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Topical Review

Applying machine learning to optical metrology: a review

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Abstract

This literature review investigates the integration of machine learning (ML) into optical metrology, unveiling enhancements in both efficiency and effectiveness of measurement processes. With a focus on phase demodulation, unwrapping, and phase-to-height conversion, the review highlights how ML algorithms have transformed traditional optical metrology techniques, offering improved speed, accuracy, and data processing capabilities. Efficiency improvements are underscored by advancements in data generation, intelligent sampling, and processing strategies, where ML algorithms have accelerated the metrological evaluations. Effectiveness is enhanced in measurement precision, with ML providing robust solutions to complex pattern recognition and noise reduction challenges. Additionally, the role of parallel computing using graphics processing units and field programmable gate arrays is emphasised, showcasing their importance in supporting the computationally intensive ML algorithms for real-time processing. This review culminates in identifying future research directions, emphasising the potential of advanced ML models and broader applications within optical metrology. Through this investigation, the review articulates a future where optical metrology, empowered by ML, achieves improved levels of operational efficiency and effectiveness.

Keywords: machine learning, artificial intelligence, neural networks, optical metrology

Nomenclature

AFS-SVM	Angle-frequency domain synchronous analysis with support vector machine
AF	Auto-focus
AU	Area under curve
AIA	Advanced iterative algorithm
BPNN	Back-propagation neural network
BUT	Branch-cut
CC	Cross correlation
CSI	Coherence scanning interferometry
CDIF	Central difference information filtering
CDLP	Composite fringe projection machine learning profilometry
CF3DNet	Circular fringe-to-3D reconstruction network
CGANs	Conditional generative adversarial networks
CMM	Coordinate measuring machine
CNN	Convolutional neural network

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CUE-NET	Convolution U network
CVT	Curvelet transform
DCAHINet	Deformable convolution-based HINet with attention connection
DCGAN	Deep convolutional GAN
DLCDIFPU	Deep learning central difference information filtering for phase unwrapping
DL-TPU	Deep learning for temporal phase unwrapping
DLPU-Net	Deep learning phase unwrapping
DOF	Depth-of-field
DNN	Deep neural networks
DRPL	Deep regression pair learning
DSMNet	Domain-invariant stereo matching network
DSC	Digital speckle correlation
DSIFT	Dense scale invariant feature transform
DTCWT	Dual-tree complex wavelet transform
DYnet++	Deep learning based single-shot phase-measuring deflectometry
FL	Federated learning
FPGAs	Field programmable gate arrays
FOV	Field of view
FPP	Fringe projection profilometry
FrANet	Fringe analysis network
FT	Fourier transform
FTP	Fourier transform profilometry
FVM	Focus variation microscopy
gAIA	Parallelised GPU-based advanced iterative algorithm
GAN	Generative adversarial network
GPU	Graphics processing unit
GWCNet	Group-wise correlation stereo network
HT	Holographic tomography
IFCNN	Image fusion framework based on the CNN
ILS	Iterative least-square
InSAR	Interferometric synthetic aperture radar
InSAS	Interferometric synthetic aperture sonar
IoU	Intersection over union
I-Net	Inception-v3 net
LS	Least squares
ML	Machine learning
MAE	Mean absolute error
MCF	Minimum cost flow
MCNet-PU	Mask cuts network phase unwrapping
MFF-GAN	Unsupervised generative adversarial network with adaptive and gradient joint constraints
MIoU	Mean intersection over union
MIMONet	Multi-input multi-output network
MPI	Message passing interface
MPCAM	Multi-point spread function camera system
MSE	Mean squared error
MW-Net	Multi-wavelength network
OpenMP	Open multi-processing
PA	Pixel accuracy
PCA	Principal component analysis
PC	Pseudocorrelation
PCTNet	Parallel CNN-transformer network
PG	Phase gradient
PhysenNet	Physics-enhanced deep neural network
PI-FPA	Physics-informed deep learning method for fringe pattern analysis
PS	Phase shifting
PSF	Point spread function
PSNR	Peak signal-to-noise ratio
PU-GAN	One-step 2D inSAR phase unwrapping based on conditional GAN
PV	Phase derivative variance
PSMNet	Pyramid stereo matching network
QGPU	Quality guided phase unwrapping
RP	Ratio of low-pass pyramid
RCNN	Recurrent classification neural network
RMSE	Root mean square errors
RU-Net	Resblocks based U-Net
Rsm	Mean profile element spacing
SAPR-DL	Single-shot multi-frequency absolute phase retrieval based on deep learning
SAR	Synthetic-aperture radar
SCAPU	Spatial and channel attention network phase unwrapping
SL	Structured light
SNAPHU	Statistical-cost, network-flow algorithm for phase unwrapping
SSGAN	Self-supervised generative adversarial network
SSIM	Structural similarity index
SSMNet	Shape-aware speckle matching network
SFPP	Single fringe-pattern processing
SwinFusion	Swin transformer
TPDNet	Texture-guided phase to depth networks
U^2-Net	Two-stage nested U-shaped structure
U-GauNet	U-Net global attention upsample
UKFPU	Kalman filtering phase unwrapping
TPU	Temporal phase unwrapping
U2Fusion	Unsupervised end-to-end image fusion network
VGG	Very deep convolutional networks
VRNet	VGG and RefineNet based network
VUR-Net	VGG, U-net, and Resnet based network
WFT	Windowed Fourier transform
μDLP	Micro deep learning profilometry

1. Introduction

Optical metrology has traditionally relied on physics-based methods to interpret interactions between light and matter for accurate dimensional assessment [1, 2]. Optical metrology is critical for ensuring the quality and accuracy of products in sectors ranging from engineering and manufacturing to biomedicine and cultural heritage conservation [3–5]. Despite the effectiveness of the physics-based methods, the evolving demands of modern manufacturing and quality control necessitate enhanced measurement speed, accuracy, and adaptability [6, 7]. ML, emerging as a pivotal technological advancement, offers potential avenues to overcome inherent limitations in traditional optical metrology through data-driven approaches, enabling enhanced efficiency and effectiveness in measurement processes [8, 9].

Optical metrology, essential for ensuring the dimensional accuracy and quality of products across various industries, faces challenges that demand advanced computational solutions. ML techniques, with their ability to learn from data, adapt to new scenarios, and make predictive analyses, stand at the forefront of these new demands, offering solutions to enhance measurement efficiency and effectiveness [10].

This review discusses the integration of ML in optical metrology, emphasising advancements in phase demodulation, phase unwrapping, and phase-to-height conversion. By harnessing the power of ML algorithms, optical metrology can overcome traditional limitations, achieving improved data processing speeds, accuracy, and adaptability to complex measurement scenarios. The synergy of ML with parallel computing, particularly GPUs and FPGAs, further exemplifies a leap in computational efficiency, enabling real-time data analysis and broadening the application spectrum of optical metrology. As we navigate through the convergence of ML and optical metrology, this introduction sets the stage for a comprehensive exploration of this integration, highlighting advancements on measurement processes, and the envisioning of a future where optical metrology improves efficiency and effectiveness.

Figure 1 illustrates the structure employed in this literature review, delineating two distinct components. Section 2 (white colour) is dedicated to efficiency improvement by ML, while section 3 (grey colour) addresses effectiveness improvement by ML. Each rectangle signifies parts of the sections in this article. Within section 2, we elucidate four ML approaches designed to enhance efficiency: data generation (section 2.1), sampling strategies (section 2.2), and ML-based metrology (section 2.3). Furthermore, we introduce end-to-end ML methodologies specifically applied to optical metrology (section 2.4). Additionally, the incorporation of parallel acceleration (section 2.5) is introduced, demonstrating potential contributions to amplifying the efficiency of ML methodologies. In section 3, we discuss methodologies for improving effectiveness through ML, focusing on phase demodulation (section 3.1), phase unwrapping (section 3.2), and phase-to-height conversion (section 3.3).

1.1. Motivation for applying ML to optical metrology

The motivation behind applying ML techniques in optical metrology comes from the limitations and challenges encountered by physics-based approaches, highlighting the necessity for efficient and effective solutions in the face of challenges posed by approaches and real-world environments. Unlike physics-based approaches, the data-driven nature of deep-learning-enabled optical metrology has offered alternative solutions to numerous challenging problems in the field, demonstrating superior performance. For example, when reliant on physics-based models mapping user-desired sample parameters to simulate images and investigate the influence of uncertainty sources cannot be ignored. Defining prior information enhanced user-dependent models can be intricate and time-consuming. Additionally [11], the intricate, multi-step measurement processes involved in optical metrology could lead to error accumulation. Moreover, the sensitivity of optical measurement to the environment, usually defined in laboratory settings, faces challenges in harsh factory environments due to physical and knowledge limitations [12–15].

The review is also motivated by several considerations:

- ML, while identifying patterns in training datasets, may not always yield provably correct solutions, posing risks in optical metrology where traceability, reliability, and repeatability are prioritised. That is a difference from many computer vision tasks [16]. In surface defect inspection, overfitted DNNs may smooth out irregularities, potentially leading to defective production runs [17].
- High-risk scenarios in optical metrology involve challenges such as noisy, inaccurate, uncertain, vague, and incomplete datasets [18], heightening the risk of prediction failure due to the inherent unexplainability and incomprehensibility of ML [19].
- Current ML approaches in optical metrology often learn solutions from massive training datasets without significant reliance on prior knowledge, contrasting with traditional physics-based methods that integrate engineered domain knowledge. Incorporating partial knowledge of physics laws into ML models is recommended to optimise training data and network parameters [20].
- The effectiveness of ML depends on the reliability of the provided training data, especially in optical metrology. Challenges in collecting high accuracy ground truth data for optical metrology, coupled with the highly customised nature of systems, resulting in few publicly available datasets, hindering fair and standardised algorithm comparisons [21].

1.2. Optical measurement technologies

Before exploring advances facilitated by ML, acknowledging the significance of established optical technologies for the measurement of surface texture and coordinates is imperative. These measurement technologies includes CSI [22–27], FVM [28], confocal microscopy, and others. Optical coordinate measurement technologies [29–31], including FPP [32–34], photogrammetry [35, 36] and laser triangulation, focus on the three-dimensional (3D) measurement of an object's physical geometry.

Although various publications have contributed to advances in surface and coordinate metrology techniques [37–44], this review emphasises ML-based optical metrology. Given the substantial advances and widespread application of optical metrology, this literature review does not delve extensively into these well-established techniques. Instead, it focuses on the synergy between ML and optical metrology, aiming to highlight the importance of data-driven models in improving key aspects of optical metrology.

2. Efficiency improvement by ML and parallel acceleration

The advent of ML and parallel computing technologies has improved the landscape of optical metrology, offering enhancements in efficiency. In this section, we discuss the

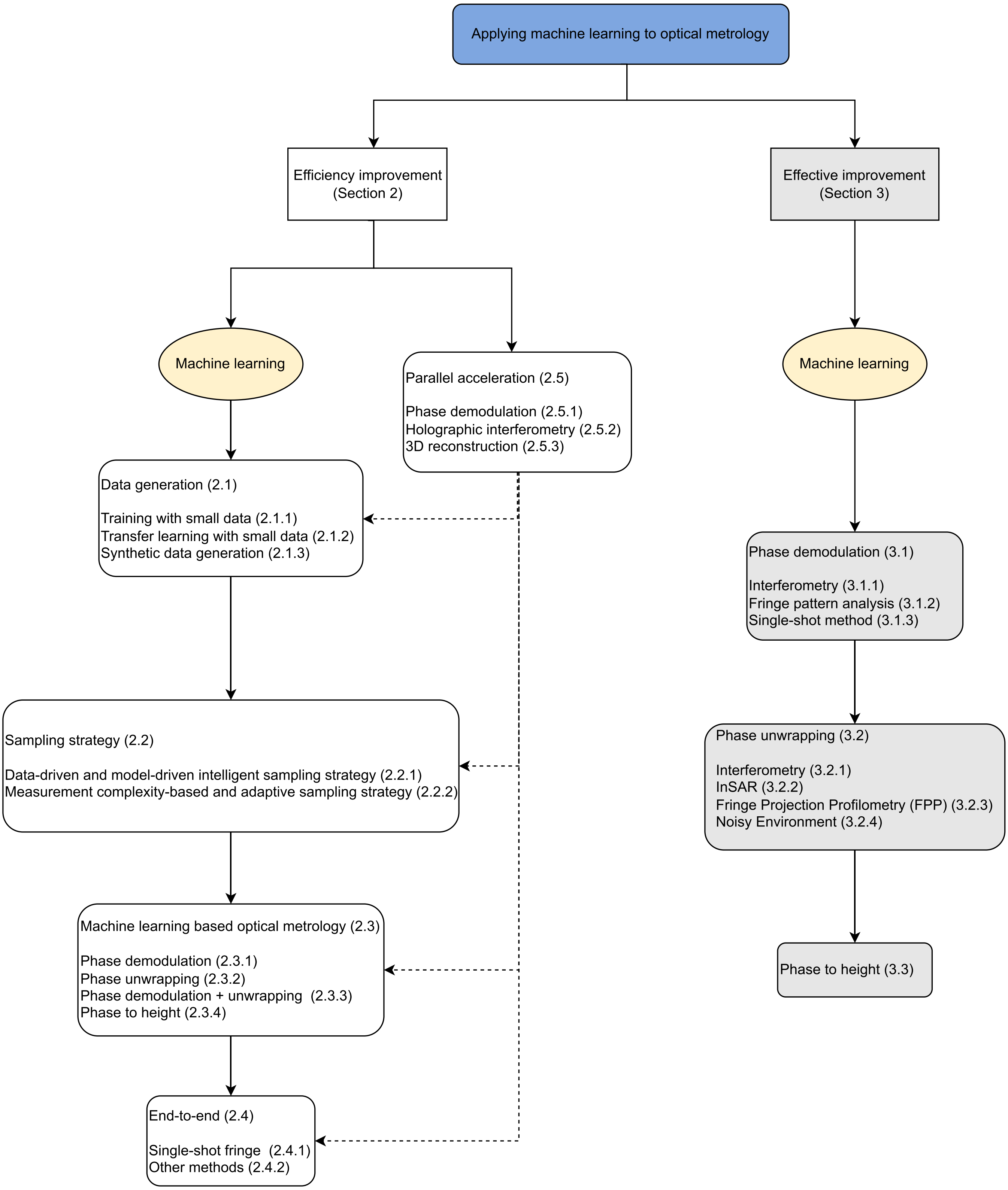

Figure 1. Structure of this literature review. Each rectangle signifies an individual section within this literature review. The presence of a dashed line signifies the prospect that parallel acceleration might also contribute to enhancing the efficiency of other sections.

role that ML methods and parallel computing frameworks play in optimising and accelerating various facets of optical metrology.

ML, with its ability to process and learn from big data, has emerged as a catalyst for improvement in optical metrology, particularly in the realms of data generation in

Table 1. Section 2.1.1: summary of methods for efficiency improvement in training with small data.

Authors	Method	Pros	Potential cons	Potential efficiency improvement
Olson *et al* [47], 2018	Ensemble of low-bias sub-networks	Smaller number of training examples	Binary classifiers focus	Reduction in variance and overfitting
Qi and Luo [48], 2020	Survey on unsupervised and semi-supervised methods	Broad analysis of methods	Limited practical application depth	Future directions for applying unsupervised and supervised learning
Bornschein *et al* [49], 2020	Empirical analysis of model performance	Robust signal for model selection	Requires large model sizes	Training on smaller subsets for computational savings
Wang *et al* [50], 2020	U-Net based model with physical model	Improved image quality and training stability	Focused on facial images	Reduced average error rates and faster image generation
Kokol *et al* [51], 2022	Synthetic knowledge synthesis	Comprehensive overview of ML challenges	Publications indexed in Scopus only	Data pre-processing and model choices for efficiency
Han *et al* [52], 2023	U-Net based self-supervised GAN model	Improved image quality on small data	Image data focus issues	The image quality is improved with a small data

section 2.1, sampling strategies in section 2.2, phase analysis in section 2.3, end-to-end ML in section 2.4 and parallel computing in section 2.5. Its application ranges from enhancing data generation methodologies to overcoming limitations posed by small data and synthetic data challenges, thereby boosting the metrological process's efficiency. Moreover, intelligent sampling strategies empowered by ML algorithms have improved the way measurements are conducted, optimising them for speed while ensuring adaptability to diverse measurement scenarios.

Together, ML and parallel computing can improve optical metrology, enhancing the field's efficiency and applicability. The following sections will explore these advances in detail, illustrating the impact of these technologies on the evolution and future trajectory of optical metrology.

2.1. ML addresses data challenges in optical metrology

We have already discussed the challenges in processing data in optical metrology in the Motivation section 1.1, as also mentioned in [11, 45, 46]. Catalucci *et al* [11] pointed out problems with measurement speed and data bottlenecks, which are important in production when measurements need to be real-time or close to real-time. These problems, usually caused by limitations in software and hardware, slow down inspections and make it hard to do real-time measurements using optical metrology. ML helps by improving how we analyse and collect data. The following sections will explore how ML helps with small data (section 2.1.1), transfer learning (section 2.1.2), and creating synthetic data (section 2.1.3). Finding better ways to create and process data makes data-driven methods more efficient.

2.1.1. Training with small data. As noted in the motivation section, challenges in collecting ground truth data for optical metrology and the customised nature of the systems lead to few publicly available datasets. Although there is a lot of research on ML with big data, interest is growing in how these methods work with small data. These papers present various methods and demonstrate how to use ML even when data is limited. We focused on identifying high-quality studies on small data in ML from the past six years, selecting only peer-reviewed articles and seminal works published in English. After reviewing the full texts, we chose six papers that represent small data in ML and its potential to be applied in optical metrology. Table 1 shows the pros and potential cons of each method.

Firstly, Olson *et al* [47] use a linear program to break down well-trained neural networks (NNs) into groups of low-bias sub-networks. They found that these low-bias sub-networks are not closely related, similar to a random forest. They apply large NNs, with hundreds of parameters per training sample, to small data and found that these networks still performed well without overfitting. Subsequently, Qi and Luo [48] focused on the challenges of using small labeled datasets in the era of big data, particularly in representation learning. They discussed unsupervised and semi-supervised methods, including generative models such as auto-encoders, GANs, flow-based models, and autoregressive models. They compared the disentanglement of unsupervised and semi-supervised representations for factorised and interpretable networks. They made a review of current methods and future potentials in efficiently utilising small amounts of labeled data for ML, emphasising the connection of unsupervised and semi-supervised techniques to enhance learning processes and model performance.

In a related context, Bornschein *et al* [49] studied how well large NNs perform across different sizes of training sets. They found that training with smaller subsets of data can not only save computational resources but also lead to more accurate decisions when choosing models. This result suggests that big NNs can keep their performance consistent with the small data set. Recent research on ML with small data, as examined by

Table 2. Section 2.1.2: summary of methodologies for efficiency improvement in transfer learning with small data.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Ng *et al* [56], 2015	Transfer learning with CNNs for emotion recognition	Utilises pre-trained networks to overcome small data issues	May not generalise well to vastly different data	Enhanced model performance with small data
Cao *et al* [57], 2018	Preprocessing-free gear fault diagnosis with CNN-based transfer learning	Simplifies the diagnostic process by eliminating preprocessing steps	Specific to gear fault diagnosis, limiting broader application	Improved fault detection speed
Brodzicki *et al* [58], 2020	Transfer learning methods in computer vision with small data	Offers a framework for applying transfer learning in vision tasks	Requires substantial computational resources for retraining	Improve classification efficiency in image-related tasks

Wang *et al* [50] introduced an approach with their PhysenNet for computational imaging in optics, specifically in the context of single-beam phase imaging. By incorporating a complete physical model, PhysenNet was shown to reduce the need for extensive training labeled data; this could potentially improve computational imaging without training beforehand.

Additionally, Kokol *et al* [51] focus on reducing dimensions, augmenting data in ML, and statistical learning on small data. This underscores the importance of complex ML approaches, due to the high cost of sampling. Finally, Han *et al* [52] introduced a training method that uses PCA and a SSGAN. This method improves image quality and stability when using small data compared to a DCGAN [53]. The proposed method includes a U-Net based structure and a modified training approach. The results show that this method can achieve the same or even better image quality and lower error rates with small datasets than with large datasets.

The six studies reviewed adapt ML techniques for small data, enhancing image quality and stability in optical metrology [47, 48, 51, 52]. Moreover, these findings promote a first-step for a data-driven approach to use ML methods in optical metrology, ensuring efficiency with limited datasets [49, 50].

2.1.2. Transfer learning with small data. Transfer learning [54] is a method in ML that involves transferring knowledge from one area (source domain) to another (target domain). This is particularly useful when the target domain does not have enough data for effective model training on its own. This technique is popular because it uses models already trained on big data, adapting them to new tasks with small data [55]. In optical metrology, where precise measurements are crucial, there often are not enough big, labeled datasets for training. Transfer learning offers a solution by using models trained on extensive datasets from similar tasks or fields. This method speeds up the training process and improves performance in environments with small data, such as in specialised metrology tasks. We focused on identifying high-quality studies on transfer learning with small data from the past nine years, selecting only peer-reviewed articles and seminal works published in English. After reviewing the full texts, we chose three papers that represent transfer learning with small data and its potential to be applied in optical metrology. Table 2 shows the pros and potential cons of each method.

Ng *et al* [56] used transfer learning with deep CNNs for recognising emotions in facial expressions, specifically for a 2015 competition about emotion recognition. They started by using a network that was pre-trained on a big data called ImageNet, and then further trained it on the competition's dataset. This approach improved their results compared to the initial ones. This highlights the importance of using big, additional datasets of facial expressions to train DNNs in this field. Building on this perspective, Cao *et al* [57] developed an approach using deep CNN and transfer learning for preprocessing-free diagnosing gear faults. Unlike traditional methods that rely on extracting features specific to the domain, this method performed better even with a small training dataset. It was more efficient in classifying faults than other methods like local CNN and AFS-SVM. This success could be widely used for fault diagnosis in optical metrology. Furthermore, Brodzicki *et al* [58] explored transfer learning as a way to overcome the problems caused by small data in machine vision tasks. Their research highlighted two main approaches of transfer learning: feature extraction and fine-tuning, which showed good results in various computer vision tests. These results demonstrate the method's wide applicability in tasks like measuring thickness, detecting anomalies, and classifying objects. However, they pointed out an issue known as negative transfer, where solutions from previous problems can make later tasks more complicated.

Transfer learning is a potential method for improving measurement systems in optical metrology, especially when dealing with small data. By applying ML, and specifically transfer learning, optical metrology can address the challenges of small data, opening up possibilities for efficiency. These studies support the use of ML in optical metrology and show how these methods can improve measurement and analysis across different scientific and industrial areas. Transfer learning allows optical metrology to use pre-trained ML models for data analysis and feature extraction, even with small data. This approach not only makes optical metrology more efficient but also saves time and resources in model training and development.

Table 3. Section 2.1.3: summary of methodologies for efficiency improvement in synthetic data generation.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Fonseca and Bacao [59], 2023	Unified taxonomy for synthetic data generation in tabular and latent spaces	Consolidates understanding and categorisation of synthetic data techniques	May overlook emerging or newest generation methods	Guides development of targeted algorithms, enhancing synthetic data application
Little *et al* [61], 2023	FL for synthetic data generation	Enhance privacy and data utilisation from multiple sources	Limited by FL's computational complexity	Improves data availability and security
Kim *et al* [62], 2023	GANs and meta-learning for wireless data generation	Reduces dataset requirements and enhances data realism	Efficiency depends on initial training data quality	Reduces overhead in wireless system data preparation
Park *et al* [63], 2023	CGANs for virtual optical image generation	Mitigates limitations of cloud coverage in image acquisition	Dependent on the quality of source SAR and optical images	Enhances crop classification and monitoring efficiency

2.1.3. Synthetic data generation. This subsection discusses how synthetic data generation is applied in optical metrology, particularly when real datasets are small or incomplete. In optical metrology, creating synthetic data allows for training ML models for tasks such as measurement and analysis. Gathering large, real datasets in this field is often difficult due to various constraints [59, 60]. Synthetic data, which simulates realistic optical measurements or features, helps enhance the performance of ML models by overcoming challenges like privacy and limited data access, often found in sensitive industrial settings. Table 3 shows the pros and potential cons of each method.

Fonseca and Bacao [59] conducted a review of synthetic data generation, focusing on tabular data, a common format in industry that is often not given enough attention. The study outlined and categorised 70 algorithms used for six different ML problems. It organised different methods of generating data, discussed how to evaluate these methods, and pointed out areas needing more research. This provides useful information for researchers who want to improve their use of synthetic data across various fields. The study emphasised the importance of synthetic data in protecting privacy and preparing data for ML uses. It identified gaps in current research and suggested directions for future studies, highlighting the role of synthetic data in modern research.

Moving to a related field, FL [64], known as collaborative learning, is a unique ML method. Unlike traditional centralised learning, FL trains an algorithm through many separate sessions, each using a different dataset. This approach does not assume that the data in all locations are the same, which is a departure from usual methods. In this area, Little *et al* [61] reviewed how FL can be used to create synthetic data. They pointed out its ability to combine data from multiple clients without risking privacy and effectively deal with issues of data access and diversity. Although this approach of federated synthesis is new and its practical value is still being evaluated, the research indicates it has potential in optical metrology. This encourages further investigation, especially in assessing privacy risks and agreeing on how to measure the risks and benefits of synthetic data.

Furthermore, Kim *et al* [62] introduced a way to collect wireless data for ML systems using a GAN and meta learning. This method creates realistic data samples, reducing the need for collecting many real samples. Their tests show that this approach efficiently trains ML models, achieving results comparable to those trained with real data. This method using meta learning is particularly relevant as we move towards the 6G era, preparing for a time when data from various but related wireless environments will increase. Similarly, Park *et al* [63] studied how to use SAR images and CGANs to create virtual, cloud-free optical images for early crop mapping. Their research shows that a two-stage CGAN method, which uses various types of input data, can classify crops as accurately as real cloud-free optical images. This highlights the potential of CGANs to overcome the common problem of cloud cover in optical images, leading to new possibilities in early crop mapping.

In this section, we have looked at how creating synthetic data is a crucial tool in ML, especially when there are not enough real datasets available [59]. The studies we discussed show how synthetic data can be used in various fields, such as optical metrology, to improve model training and prediction efficiency [61]. By creating realistic data, researchers can address issues like limited sample sizes, privacy concerns, and varied data types, thus advancing ML applications in fields that require high precision, like optical metrology. The use of ML in generating synthetic data, as shown in these papers, improves analysis, protects data privacy, and makes models more widely applicable in optical metrology. By creating realistic and specific datasets, ML not only fills the gaps where actual data is lacking but also potentially makes optical metrology more reliable. The findings from these studies suggest an increase in efficiency, where insights are derived with less reliance on traditional data collection, which is often expensive, time-consuming, and influenced by external factors [62, 63]. Ultimately, incorporating ML into synthetic data

Table 4. Section 2.2.1: summary of methodologies for efficiency improvement in data-driven and model-driven intelligent sampling strategy.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Yang *et al* [65], 2021	Data-driven intelligent sampling	Adapts to surface complexities	Requires big data for training	Reduction in measurement time and resources
Lu *et al* [66], 2019	Uncertainty-guided sampling with free-knot B-splines	Enhances efficiency in uncertain areas, optimises for complex surfaces	Computational intensity for spline model optimisation	Improved sampling efficiency
Ren *et al* [67], 2021	Generative model-driven strategy	Use generative models for informed sampling, efficient in complex surfaces	Dependent on generative model accuracy	Reduction in unnecessary sampling, enhanced speed

generation provides better efficiency, scalability, and adaptability in optical metrology.

2.1.4. Discussion about section 2.1: ML for data generation.

The use of ML in different aspects of data generation in optical metrology shows a move toward advanced and informed measurement practices. By incorporating ML in areas like small data and synthetic data generation, the field improves its ability to analyse data efficiently and flexibly. From the studies we reviewed, it is clear that ML is key to overcoming traditional data challenges, opening additional ways to gain deeper insights into measurements. This could lead to a shift where data science and optical metrology together enhance how we understand and manage measurements. Thus, optical metrology is ready to benefit from ML in tackling the complexities of data generation and analysis.

2.2. ML in sampling strategy

In optical metrology, using ML to improve how samples are taken is an improvement in measurement techniques. The research we reviewed shows a trend towards using ML to make sampling in complex surface measurements more efficient. This introduction compares traditional static methods with dynamic, intelligent ML approaches, showing how they have improved the field. These developments are crucial for overcoming the complex challenges in modern manufacturing, and they provide a look at how ML strategies can speed up optical metrology.

The following discussion discusses sampling methods used in 3D surface measurement for smart manufacturing. It includes an analysis of data-driven and model-driven approaches [65] (section 2.2.1), which use existing data to improve the sampling process. The discussion also covers model-driven strategies [66, 67], where predictive models help guide sampling methods, useful in dealing with uncertainties when reconstructing surfaces. Additionally, the review looks at the influence of the measurement area [68], highlighting how space considerations affect sampling decisions (section 2.2.2).

2.2.1. Data-driven and model-driven intelligent sampling strategy.

The use of ML in optical metrology marks a change towards efficient measurements. The three papers we reviewed explore both data-driven [65] and model-driven [66, 67] approaches. These studies show that ML can improve sampling strategies, enhance measurement processes, and adjust to different surface shapes and complexities. Table 4 shows the pros and potential cons of each method.

In their study, Yang *et al* [65] gave a review of data-driven methods, focusing on how these methods can interpolate and plan sampling for 3D surface measurements. This research highlights the increasing role of data analytics in manufacturing, especially how it helps overcome the high costs and long times needed for acquiring detailed surface data. The paper also points out key areas for future research to better connect academic studies with real-world industrial use in the growing field of smart manufacturing. Lu *et al* [66] developed a sampling strategy based on uncertainty of under-defined areas for efficient surface measurement. They used a smart model based on free-knot B-splines, which showed good performance in their tests on both simulated and real surface data. This method is particularly suitable for surfaces with sparse and sharp features and reduces computing time. Ren *et al* [67] introduced a new generative model-based strategy for CMMs, aimed at more efficiently checking machining errors on complex surfaces. Their approach, which uses sparse sampling and ML model, cuts down sampling time while maintaining accuracy.

2.2.2. Measurement complexity-based and adaptive sampling strategy.

In optical metrology, the efficiency of different sampling methods affects the accuracy and reliability of measurements. It's important to explore various sampling strategies to improve the efficiency of optical metrology. This review introduces two methods: one examines how the size of the measurement area affects metrological results [68], and the other uses a NN-based adaptive sampling technique for surfaces with high uncertainty [69]. This introduction highlights how sampling strategies have evolved from static to dynamic models to meet the needs of optical metrology. Table 5 shows the pros and potential cons of each method.

Table 5. Section 2.2.2: summary of methodologies for efficiency improvement in measurement complexity-based sampling and adaptive sampling strategy.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Bazan *et al* [68], 2023	Analysis based on the SCR and Rsm parameters to determine the measurement area	Introduces parameters to optimise measurement area selection	The method's effectiveness may be influenced by material properties	Optimising the measurement area can lead to faster measurements
Gao *et al* [69], 2023	Adaptive sampling using BPNN to predict responses and select the next best point	Enhances surface reconstruction efficiency by dynamically adapting sampling points	May require large computational resources for NN training	By intelligently adapting sampling points, the method could reduce the number of measurements needed

Bazan *et al* [68] studied how the measurement area size affects the topography of samples made through additive manufacturing. Using the focus variation method, they compared large and small measurement areas and found differences in measurements from random-type samples, showing the importance of choosing the right measurement area size. They suggested that using multiple smaller areas could provide better insights into variability for samples with directional textures. The study calls for more research on selecting measurement areas in surface topography analysis, especially focusing on the usefulness of the Rsm parameter and other potential solutions. Similarly, Gao *et al* [69] developed an adaptive sampling strategy that uses a BPNN to predict the geometric features at potential measurement points. This method combines predictions with the MaxCWVar criterion to choose the most effective next measurement point. It proved useful strategy for modelling complex surfaces with high uncertainty.

Overall, the studies reviewed show a possibility to apply adaptive techniques in optical metrology [68, 69]. Using NN-based adaptive sampling marks an advancement, improving efficiency in dealing with uncertain surfaces. This change enhances our understanding of measurement efficiency and expands the possibilities for applying optical metrology in complex situations. Future research should explore how ML can be integrated into optical metrology to open up new possibilities for efficiency.

2.2.3. Discussion about section 2.2: ML in sampling strategy. The use of ML in optical metrology represents a change towards more advanced and smart methods. The papers reviewed show how the industry is moving from fixed ways to flexible strategies that better suit the detailed and complex surfaces being measured. ML plays a role in this change by quickly processing and analysing big data, which helps make the sampling process more efficient and specific. This progress is an important development in the field, leading to more efficient and adaptable ways of working in the future. These studies highlight how ML can improve sampling strategies, setting the stage for smarter and more efficient optical metrology.

2.3. ML based optical metrology

In this section, we discuss how combining ML with optical metrology improves measurement efficiency. The studies show a shift from traditional methods to more dynamic, intelligent strategies that enhance efficiency. ML speeds up operations, cuts costs, and improves data interpretation in optical metrology. For example, Eastwood *et al* [29, 70] highlighted the role of high-performance computing in integrating ML, which has contributed to faster 3D imaging and more efficient phase unwrapping techniques. In this context, this section highlights how the optical metrology is evolving, particularly in areas such as phase demodulation (section 2.3.1), phase unwrapping (section 2.3.2), phase demodulation plus unwrapping (section 2.3.3), and phase-to-height conversion (section 2.3.4). It emphasises how ML can simplify and improve these aspects of optical metrology, making the processes more efficient.

2.3.1. Efficiency improvement in phase demodulation. In this subsection, we discuss how ML improves the process of phase demodulation, a step in optical metrology that affects the speed of 3D surface measurement. Table 6 shows the pros and potential cons of each method.

The integration of ML and physics-informed algorithms in phase demodulation is illustrated by Feng *et al* [71] developed a method called µDLP, a fast 3D surface imaging technique that uses ML. This method stands out for its efficiency and ease of use compared to other high-speed imaging methods, like those based on Fourier-transform. The results show that µDLP could advance 3D imaging for fast-moving objects and may help merge high-speed 3D imaging with high-rate 2D photography. In a related vein, Yin *et al* [72] introduced a method called PI-FPA, which uses physics-informed ML to quickly reconstruct phases from single shots in optical metrology. By combining traditional methods with ML, PI-FPA achieves fast phase demodulation and adapts well to new types of samples. This approach is beneficial for speeding up processes in optical metrology by blending physics-based methods with ML. Furthermore, Nguyen *et al* [73] have developed DYnet++, a ML method for real-time 3D shape measurement

Table 6. Section 2.3.1: summary of methodologies for efficiency improvement in phase demodulation.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Feng *et al* [71], 2019	μDLP for 3D surface imaging	High-speed imaging, rapid phase extraction	May require extensive training data	Reduces acquisition time via quick profilometry
Yin *et al* [72], 2023	PI-FPA	Computationally efficient phase reconstruction, interpretability	Higher computational complexity	Balances efficiency with physical insights
Nguyen *et al* [73], 2023	DYnet++ for single-shot phase-measuring deflectometry	Efficient single-shot measurements	Handling non-specular surfaces	Measure different free-form surfaces with high speed and even in real-time

in deflectometry. This method makes the phase demodulation process fast and automated for measuring complex surfaces with low reflectivity, ideal for industrial use in real-time.

In conclusion, using ML in phase demodulation enhances efficiency in optical metrology [71–73]. These techniques handle big data and integrate physical principles to refine the phase demodulation process and address more complex optical metrology challenges. As these technologies evolve, they are expected to boost the efficiency of optical metrology systems, leading to faster and more reliable optical metrology analyses and applications.

2.3.2. Efficiency improvement in phase unwrapping. We explore how ML can make phase unwrapping faster and more reliable. Phase unwrapping is a step in optical metrology that can be time-consuming. Table 7 shows the pros and potential cons of each method.

Yin *et al* [74] used ML for TPU (DL-TPU) not only makes the process more reliable, even with complex patterns, but also speeds up 3D surface imaging. Interestingly, their study suggests that DL-TPU could also be used in other types of 3D surface imaging, expanding its usefulness in optical metrology. Additionally, Li *et al* [75] developed a quick 2D phase unwrapping algorithm that uses a NN to predict errors and adjust gradients. This method is designed to be fast and accurate, which makes it useful for techniques such as InSAR and InSAS, where quick processing is essential. At the same time, Liu *et al* [76] tackled the challenge of efficient 3D shape measurement with a phase unwrapping method based on ML. This method combines composite fringe coding and stair phase coding to allow quick 3D reconstructions from a small number of images, effectively handling issues like defocus and noise.

Together, these studies show how ML can enhance phase unwrapping in 3D imaging processes. They have improved efficiency and simplified the computational work involved, showing potential for the use of ML in this field. Future research could further enhance these methods, leading to more efficient phase unwrapping techniques.

2.3.3. Efficiency improvement in phase demodulation plus unwrapping. The integration of ML in optical metrology, particularly in the context of phase demodulation plus unwrapping, represents an advancement in this field. Table 8 shows the pros and potential cons of each method.

Nguyen *et al* [77] developed a 3D reconstruction method that combines SL techniques with a deep learning NN. Their method uses a single SL image and a dual-output network to create multiple phase-shifted fringe patterns and a coarse phase map quickly. Following this, Yang *et al* [78] introduced a NN called a RCNN to tackle the challenges of reconstructing complex scenes. This network, which is both robust and efficient, simplifies the process by using only two fringe patterns. It turns the complicated steps of phase recovery and unwrapping into a simpler task of phase classification. This change makes it easier to perform real-time 3D reconstructions.

In conclusion, these studies show that ML enhances the efficiency of phase demodulation plus unwrapping in optical metrology. These improvements not only make the measurement processes more reliable but also expand the possibilities for real-time and on-site monitoring.

2.3.4. Efficiency improvement in phase-to-height conversion. Recent improvements in phase-to-height conversion have highlighted the role of ML in enhancing efficiency. The move from traditional methods to those using ML and mixed network structures marks a change towards advanced techniques. ML models, especially those that combine CNNs and transformers, have potential in making the phase-to-height conversion processes in optical metrology more efficient [79–81]. Table 9 shows the pros and potential cons of each method.

Yupeng *et al* [79] introduced a simulation-driven ML approach for rapidly correcting slope-dependent errors in CSI measurements, addressing a challenge in characterising complex engineering surfaces. Importantly, by employing a DNN trained on simulated surface topography measurements from a physics-based virtual CSI, the proposed method achieved slope-dependant error correction for a 1024×1024 sampling point surface height map within 0.1 s, covering a FOV of $178\,\mu\text{m} \times 178\,\mu\text{m}$. Comparative analyses further demonstrate its accuracy, which is comparable to the traditional phase inversion method used to correct the slope-dependant

Table 7. Section 2.3.2: summary of methodologies for efficiency improvement in phase unwrapping.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Yin *et al* [74], 2019	Utilises DL for TPU	High reliability, effective against various error sources	May require substantial training data	Reduces error rates, enables high efficiency 3D imaging
Li *et al* [75], 2023	Combines NN with path-based algorithm	High computational efficiency, suitable for real-time processing	May has integration complexity	Speeds up unwrapping process, adaptable to real-time systems
Liu *et al* [76], 2023	Applies DL in binocular SL systems	Enhanced robustness, simplifies 3D reconstruction	May dependent on training data quality	Decreases required fringe patterns

Table 8. Section 2.3.3: summary of methodologies for efficiency improvement in phase demodulation plus unwrapping.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Nguyen *et al* [77], 2023	Single-input dual-output network	Simplifies the 3D reconstruction process using a single image	Depend on specific configurations	Beneficial for quick, single-shot analysis
Yang *et al* [78], 2024	Employs a RCNN for 3D imaging	Reduces data complexity with only two fringe patterns needed	Limited by the RCNN's specificity	Enhances efficiency and simplifies 3D imaging, suitable for real-time applications

Table 9. Section 2.3.4: summary of methodologies for efficiency improvement in phase-to-height conversion.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Yupeng *et al* [79], 2023	DNN for correcting slope-dependent errors in CSI	Fast and maintains accuracy	May require specific training data	Speeds up surface height map correction
Zhu *et al* [80], 2022	Wavelet-CNN integration for fringe pattern analysis	Reduces computational complexity	May require complex preprocessing	Improves computational efficiency in FPP depth estimation
Zhu *et al* [81], 2023	PCTNet combining CNN and transformer for SL images	Integrates local and global features efficiently	Potentially high computational resource requirement	Enhances measurement efficiency, suitable for real-time applications

error, while exhibiting a remarkable two orders of magnitude improvement in computational efficiency. Significantly, this approach holds potential for enhancing measurement efficiency on high slope and discontinuous grating surfaces, contributing to the advancement of online CSI measurements. Furthermore, Zhu *et al* [80] introduced a phase-to-height conversion method using wavelets in ML for converting from a single pattern in 3D measurements. This method simplifies the computing process, outperforming traditional ML models including U-Net [82, 83] and H-Net [84] in both qualitative and quantitative assessments. Additionally, Zhu *et al* [81] developed a PCTNet, a network that combines CNNs and transformers for converting phase-to-height conversion from SL images. PCTNet is efficient and has shown excellent results in evaluations, improving measurements in complex scenes.

These studies highlight how ML is applied in phase-to-height conversion, making it faster and more reliable. The use of advanced ML techniques and network architectures marks an improvement in performance. These developments open possibilities for real-time 3D measurements [79–81].

2.3.5. Discussion about section 2.3: ML based efficiency improvement. In conclusion, this section shows how using ML in optical metrology is contributing to more efficient and advanced measurement processes. ML has not only been applied in specific studies but has also improved the overall efficiency and capabilities of the field. By examining and comparing the different methods and results from the studies we reviewed, it is clear that ML is crucial for advancing optical metrology. Looking ahead, future research may focus on improving these ML methods, discovering new uses, and better integrating ML with optical measurement techniques. This will help ensure ongoing progress and innovation in optical metrology.

Table 10. Section 2.4.1: summary of methodologies for efficiency improvement in single-shot fringe analysis through end-to-end.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Song and Wang [85], 2023	DCAHINet	Leverage dual-stage hybrid network for FPP	Potential complexity and computational demands	Simplify network architecture while maintaining performance
Ravi and Gorthi [86], 2023	LiteF2DNet	Offer a lightweight framework suitable for low fringe frequencies	May struggle with highly complex fringe patterns	Suitable forreal-time 3D reconstruction
Ravi and Gorthi [87], 2023	CF3DNet	Improve 3D reconstruction efficiency with circular fringes	Specificity to circular fringes may limit application scope	Improve the development of a cost-effective fringe projection system
Nguyen *et al* [94], 2022	Different SL patterns analysis	Conduct further investigations on unexplored SL patterns for broader applications	Less rigorous and theoretical analysis on how the 2D-to-3D network learns	Provide guidelines for SL pattern selection enhancing efficiency
Gu *et al* [93], 2023	High-capacity spatial SL system	Enhance coding density for more robust feature detection	Increased decoding difficulty due to denser coding points	Develop more efficient decoding algorithms to handle higher coding densities
Dong *et al* [92], 2023	Speckle matching network	Achieve edge-preserved 3D measurements with speckle correlation	High GPU requirements for training and inference	Optimise network to reduce computational load

2.4. End-to-End ML to optical metrology

This section focuses on how end-to-end ML has enhanced efficiency in 3D reconstruction. It covers a range of strategies, including DCAHINet [85], LiteF2DNet [86], CF3DNet [87], CUE-NET [88], and SSMNet [89]. Each of these methods addresses specific challenges in optical metrology, such as analysing single-shot FPP and circular fringes (section 2.4.1), and cross-domain 3D reconstruction (section 2.4.2). These approaches have not only overcome traditional limitations but also combined computational power with optical accuracy, making optical metrology more efficient. We will explore the details of each method, highlighting how ML has become essential in improving the efficiency of optical metrology.

In the section 2.4.1 on single-shot fringe analysis, DCAHINet and CF3DNet two NN methods in enhancing 3D reconstruction, and efficiently handling issues like discontinuous objects. LiteF2DNet offers a fast, lightweight option for 3D reconstruction. In another section 2.4.2 that looks at broader applications, CUE-NET excels in multi-scale hologram reconstruction, while SSMNet is noted for its shape-aware speckle matching, showing how these advances are useful in various applications. Additionally, the MPCAM [90] is notable for learning multi-PSFs and performing end-to-end generative image fusion [91], improving imaging performance in different contexts.

2.4.1. Single-shot fringe analysis through end-to-end ML.

Adding ML to optical metrology, especially in techniques like single-shot fringe analysis, has advanced 3D reconstruction methods. Researchers have shifted from traditional, multi-step processes to more advanced, end-to-end ML systems. This change has unlocked new possibilities in FPP and SL methods, leading to more efficient measurement [85–87, 92–94]. Table 10 shows the pros and potential cons of each method.

Song and Wang [85] introduced a hybrid network called DCAHINet, a NN designed for FPP. This network has improved the efficiency of 3D reconstructions, especially in environments with noise and objects that do not have continuous surfaces. DCAHINet uses special techniques called deformable convolution and attention blocks to better extract and combine features from images, distinguishing it from other methods like ML models (U-Net [82] and H-Net [84]) and traditional approaches (phase shift method and multi-frequency heterodyne). These improvements not only enhance the network's ability to extract and merge features but also make it more adaptable and efficient at processing complex images. This is particularly useful in noisy situations with many interruptions. Therefore, DCAHINet has become a tool in industries that need quick and dependable optical metrology solutions.

Following this, Ravi and Gorthi [86] introduced LiteF2DNet, a lightweight learning framework end-to-end DNN designed for fast 3D reconstruction using FPP. This model is especially efficient because it requires little memory, making it much faster than traditional FPP methods like FTP [95] and WFT [96]. Its design helps improve the speed of optical measurements, particularly in real-time situations. At the same time, Ravi and Gorthi [87] developed a ML method called CF3DNet. This network directly connects changes in the pattern (phase deformations) to phase shifts, leading to better performance and lower costs compared to older methods like FTP, WFT [96, 97] and others. This technique makes the process of analysing patterns simpler, reduces errors

Table 11. Section 2.4.2: summary of methodologies for efficiency improvement in other methods through end-to-end.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Sun *et al* [101], 2023	Visual Pretraining Analysis	Investigate the impact of visual pretraining on end-to-end reasoning in ML	Specific visual pretraining may not apply to all ML scenarios	Explore broader application and integration of pretraining
Kou *et al* [90], 2023	Integrated MPCAM	Offer extended DOF in imaging with high SNR, integrating AF function for improved imaging	Performance may rely on the quality of input images	Adapt network to diverse imaging conditions for robustness
Wang *et al* [88], 2023	CUE-NET	Faster and higher quality reconstruction	Possible big data requirement for training	Reconstruct large FOV holograms in real-time.
Nguyen *et al* [102], 2021	MIMONet	Enhance 3D reconstruction efficiency using SL and ML.	Dependent on high-quality labeled data for training	MIMONet allows the balance of speed and accuracy
Li *et al* [103], 2023	Adversarial Attack Framework	Introduce an adversarial attack approach in 3D face recognition, showcasing end-to-end attack adaptability	Attack may not generalise well across different 3D recognition systems	Improve the efficiency of attacks across systems
Dong *et al* [89], 2024	SSMNet	Improved efficiency and robustness in cross-domain 3D reconstruction	Possible overfitting to specific domains	Enhance domain variability in training data

especially in images with gaps or breaks, and improves the efficiency of the entire system in collecting and processing measurement data.

In another study, Nguyen *et al* [94] explored how choosing different SL patterns affects the process of converting 2D images into 3D models using ML. Their research highlights the importance of selecting the right light patterns to improve the entire 3D reconstruction process. They found that high-frequency fringe and grid patterns work better than others, making the network more efficient in turning 2D images into 3D models. Choosing the right patterns can lower the computing needs and speed up the creation of 3D models.

Moreover, Gu *et al* [93] addressed the challenge of producing detailed and efficient 3D models using spatial SL. They introduced a method that creates pseudo-2D patterns and uses ML to detect corners automatically. This approach speeds up data processing, making the measurement results faster and more reliable, which is crucial for high-efficiency requirements. Similarly, Dong *et al* [92] presented a new speckle matching network that uses DSC [98] to measure 3D shapes quickly while preserving detail. This network performs better than older methods like GC-Net [99] and StereoNet [100], reducing the time it takes to process data and ensuring high accuracy, making it suitable for industrial needs.

The use of ML in single-shot fringe analysis methods has advanced optical metrology, making it more robust and less complex. These improvements have not only made 3D reconstruction more efficient, even in noisy environments and at low fringe frequencies, but they have also made it possible to develop faster and more cost-effective optical metrology systems. Looking ahead, future research aims to apply these methods to more complicated real-world problems, achieving real-time, dynamic 3D reconstructions, and expanding their use in both industrial and scientific settings in optical metrology.

2.4.2. Other methods incorporating end-to-end ML. The reviewed studies indicate a diverse exploration into enhancing 3D reconstruction and measurement efficiency through advanced ML frameworks. Table 11 shows the pros and potential cons of each method.

Sun *et al* [101] investigated the role of visual pretraining [104] in achieving end-to-end visual reasoning using general-purpose NNs. The results suggested that pretraining is essential for compositional generalisation in visual reasoning tasks, challenging the belief that explicit visual abstraction is necessary, and showcasing the feasibility of NN 'generalists' for solving such tasks. The approach can improve the efficiency of the model's performance by enabling it to learn more robust and generalisable representations of visual data. This means that with appropriate pretraining, the network might achieve higher accuracy or better reasoning capabilities with less data or fewer training iterations. By using self-supervised pretraining, the network leverages unlabelled data, which can be more abundantly available than labeled data. This approach could make the learning process more efficient, requiring less manually labeled data to achieve high performance. In summary, the techniques improve the efficiency of the model's learning and reasoning capabilities, potentially reducing the need for large labeled datasets and improving the model's performance on complex tasks.

Meanwhile, Kou *et al* [90] presented an integrated multi-PSF camera (MPCAM) system with AF functionality that combines multi-PSF [105] learning and end-to-end generative image fusion network to achieve large DOF and high SNR imaging. The results demonstrated that this system outperforms traditional image fusion methods such as DTCWT [106], RP [107], DSIFT [108], CVT [109], DRPL [110], unsupervised GAN with adaptive and gradient joint constraints (MFF-GAN) [111], IFCNN [112], U2Fusion [91] and cross-domain long-range learning with SwinFusion [113], making it suitable for optical metrology. The integration of an AF function driven by ML streamlines the imaging process, making it more efficient.

Furthermore, Wang *et al* [88] introduced an end-to-end reconstruction method called CUE-NET for multi-scale holograms. CUE-NET uses ML to quickly reconstruct the phase and amplitude of holograms, even when they are out of focus. It improves the speed of the reconstructed images, performing better than current methods, such as U-NET. By integrating ML, the method efficiently recovers phase information from holograms, addressing challenges like noise and data loss in traditional approaches. The technique demonstrates enhanced reconstruction speed, achieving better performance in terms of PSNR and SSIM compared to conventional methods. The ability to reconstruct large FOV holograms at different scales in real-time offers improvements in digital holography, enabling rapid analyses.

Nguyen *et al* [102] worked on making 3D shape reconstruction more efficient using ML. They integrated SL patterns into a comprehensive NN, improving the final quality through a refinement process. Their multi-input multi-output network, called MIMONet, showed promising results in tests for robustness and efficiency. By using ML, MIMONet automatically improves the 3D reconstruction process, making it more efficient. This method has the potential to replace more expensive and time-consuming traditional measurement techniques in optical metrology, offering an efficient alternative. Similarly, Li *et al* [103] introduced SL attack for 3D face recognition that incorporates 3D reconstruction and skin reflectance in an end-to-end optimisation process. This method allows for the perturbation to be integrated into the original patterns seamlessly, enhancing the efficiency of creating adversarial examples in optical metrology. This approach substitutes the traditional 3D reconstruction algorithm with a differential one, addressing the challenge of discrete pixel coordinates and enabling end-to-end optimisation for adversarial example generation. The experimental results demonstrated the efficiency of this method in attacking 3D face recognition systems with higher success rates and fewer perturbations compared to previous physical 3D adversarial attacks.

Finally, Dong *et al* [89] presented an end-to-end SSMNet that enhances efficiency and completeness in cross-domain 3D reconstruction, outperforming other vision algorithms including PSMNet [114], GWCNet [115] and DSMNet [116] in diverse contexts, and achieving highly precise 3D shape measurement in industrial scenarios. The SSMNet combines shape-mask information, cascade attention mechanisms [117], shape-aware modules, multi-scale features, and hybrid loss functions to improve the network's performance, demonstrating state-of-the-art results in cross-domain applications.

The application of ML in optical metrology, suggests a trajectory toward automated and adaptive optical measurement solutions. The integration of ML not only augments the resolution and speed of optical metrology tasks but also broadens the scope of their applicability.

2.4.3. *Discussion about section 2.4: end-to-end ML to optical metrology.*

In conclusion, the insights garnered from the reviewed studies, it becomes evident that ML's role in optical metrology is expansive. The methodologies discussed herein, from DCAHINet's dual-stage hybrid approach to SSMNet's shape-aware speckle matching, improving the efficiency and flexibility of 3D reconstruction. By analysing these advancements, one can discern a clear trend toward more integrated, robust, and adaptable systems that leverage the full potential of ML. As ML continues to evolve, its integration with optical metrology is anticipated to yield more efficient and reliable measurement systems.

2.5. *Enhancing efficiency through parallel computing*

This section discusses how parallel computing, using technologies like GPUs and FPGAs, is applied in optical metrology. It explains that these technologies improve how quickly data can be processed, allowing for analyses to happen in real-time. The text covers different uses of parallel computing in areas such as phase demodulation (section 2.5.1), holographic interferometry (section 2.5.2), and 3D reconstruction (section 2.5.3). These methods are not only faster but also easier to access. There are specific sections that go into more detail on certain topics. For example, one part discusses how GPUs can rapidly process certain types of light patterns, which speeds up computations. Another part talks about using GPUs in a method called holographic interferometry to increase efficiency. There's also a mention of a system that measures 3D shapes in real-time, which is easy to use and showcases the broad potential of these computing technologies. Finally, the review touches on other uses like improving analysis of light patterns and speeding up algorithms for computer vision, emphasising how parallel computing makes optical metrology quicker, more efficient, and less expensive.

2.5.1. *Parallel computing in phase demodulation.*

These three papers discuss the utilisation of GPU-based parallel computing for improving the efficiency of phase demodulation in optical metrology. The first paper by Wang *et al* [118] introduced a comprehensive and (GPU)-based framework for accelerating SFPP, addressing the increasing computational load posed by high-resolution fringe patterns. The proposed framework, the first of its kind, showcased speedup compared to CPU-based processing and demonstrated the importance of GPU-based processing for handling big data and high-resolution images in SFPP. On the other hand, the paper by Chen *et al* [119] addressed the issue of slow computation speed in the AIA for phase extraction by introducing

Table 12. Section 2.5.1: summary of methodologies for efficiency improvement in phase demodulation through parallel computing.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Wang *et al* [118], 2019	Comprehensive GPU-based SFPP framework	Framework-level parallelisation	Potentially less optimised for specific algorithms	Framework adaptability and potential integration of ML for optimisation
Chen *et al* [119], 2021	Fully gAIA without compromising accuracy	Up to 500 times faster than CPU and 10 times faster than partial GPU methods	Possibly limiting broader applicability	ML could optimise gAIA's performance or broaden its applicability
Zhong *et al* [120], 2023	Real-time phase demodulation using ImageJ plugin and CUDA streams	Real-time processing, improved speed for dual-wavelength holography	Possibly dependent on specific software	Improved real-time phase reconstruction speed

Table 13. Section 2.5.2: summary of methodologies for efficiency improvement in holographic interferometry through parallel computing.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Pandey *et al* [121], 2021	GPU-accelerated state space approach for rapid estimation of interference phase and its derivatives in digital holographic interferometry	Computational efficiency improvement, enabling dynamic metrology applications	Potential limitations with fringe abnormalities	Potential integration of ML for optimising processing strategies and enhancing efficiency
Munera *et al* [122], 2022	Dual-wavelength acquisition strategy to avoid numerical phase unwrapping, using GPU acceleration for processing	Optimisation of dual-wavelength strategy or ML integration for improved computational efficiency	Potential limitations in FOV	High-speed measurements by avoiding numerical phase unwrapping, speeding up the processing time

a fully parallelised GPU-based version (gAIA). gAIA accelerated AIA, achieving a $500\times$ speedup compared to CPU implementation and real-time phase extraction, all without compromising accuracy. At the same time, the gAIA's computation speed remained relatively unaffected by the frame number used. The third paper by Zhong *et al* [120] presented an ImageJ plug-in designed for real-time phase reconstruction in digital holographic interferometry. By utilising GPU and CUDA architectures and optimising data processing using CUDA streams, the plug-in improved the reconstruction speed, making it suitable for real-time applications in digital holography. Table 12 shows the pros and potential cons of each method.

In conclusion, the three papers show that using GPU-based parallel computing can improve the efficiency of phase demodulation processes in optical metrology. ML could make these methods even better by optimising the steps in the computation, automating the choice of parameters, and possibly finding more efficient ways to use GPU capabilities for phase demodulation.

2.5.2. Parallel computing in holographic interferometry. These papers focus on improving how fast and efficiently computers can process holographic interferometry. Particularly, Pandey *et al* [121] introduced a method that quickly calculates the phase of interference and its changes using GPU processing. This technique speeds up computations, making it useful for measuring changes in objects without touching them and for testing materials without damaging them. On a related note, Munera *et al* [122] showcased a high-speed micro-deformation measurement technique. This technique, distinct in its use of dual-wavelength digital holographic interferometry and the CUDA [123, 124] parallel computing framework. It also quickly reconstructs phase maps without the extra step of phase unwrapping. This is especially helpful for real-time measurements, such as vibration analysis. Table 13 shows the pros and potential cons of each method.

In conclusion, both studies demonstrate the benefits of using GPU technology to speed up the processing of holographic data. These improvements could be further advanced by incorporating ML to refine processing methods, better manage data, and improve efficiency in holographic interferometry. This could lead to possibilities in real-time optical metrology.

2.5.3. Parallel computing in 3D reconstruction. The integration of parallel computing in 3D reconstruction has advanced the field of optical metrology, offering improvements in

Table 14. Section 2.5.3: summary of methodologies for efficiency improvement in 3D reconstruction through parallel computing.

Author	Method	Pros	Potential cons	Potential efficiency improvement
Karpinsky *et al* [125]	GPU-based system for real-time 3D shape measurement	High-speed 3D shape measurement with reduced CPU load	May require specific GPU compatibility	Potential integration of ML to adapt processing strategies.
Zhang *et al* [126] 2023	Method to accelerate 3D point cloud derivation by avoiding matrix inversion	Use of ML to refine pre-computation strategies	May not generalise across all data types or hardware	15-fold increase in computational speed without additional memory overhead

processing speeds and data handling capabilities. Table 14 shows the pros and potential cons of each method.

Karpinsky *et al* [125] introduced a system that can measure the shape of 3D objects quickly, capturing 30 frames every second, with each frame containing 480 000 measurement points. This system is run on a laptop using GPU processing, which makes it portable and easily accessible to the general public for 3D shape measurements. On a related note, Zhang *et al* [126] developed a method for measuring 3D shapes that increases the speed of calculations by 15 times without additional memory. This method avoids complex mathematical steps (like matrix inversion), is easy to adapt to various 3D measurement technologies, and can be integrated into different software platforms. Additionally, it can be enhanced with parallel computing tools such as MPI, OpenMP, and CUDA, and it can be adapted into a format that uses less memory.

In conclusion, both papers showcase how parallel computing can speed up the process of 3D reconstruction. Integrating ML could improve these methods further by optimising algorithms, automating the selection of settings, and even predicting and fixing errors in real time. This could enhance the efficiency and range of applications of 3D reconstruction in optical metrology.

2.5.4. Discussion about section 2.5: enhancing efficiency through parallel computing. This section discusses the influence of ML and parallel computing on improving optical metrology, a field that deals with precise measurements using light. It highlights that these technologies are not just additional tools but are crucial to the ongoing advancements in the field. They increase the speed of computations and broaden the scope of what can be achieved with optical metrology. This emphasises the importance and potential of further integrating these technologies. Future research and developments in optical metrology will benefit from focusing on optimising these computational techniques.

3. Effectiveness improvement by ML

This section details how ML improves effectiveness of optical measurements. It covers areas like phase demodulation (section 3.1), phase unwrapping (section 3.2), phase-to-height conversion (section 3.3), showcasing a wide range of ML strategies used for 3D reconstruction. In phase demodulation (section 3.1), the discussion includes various strategies like CNN-based analysis of interference patterns, advanced analysis of fringe patterns using ML, and cutting-edge single-shot methods for precise measurements. For phase unwrapping (section 3.2), the applications in different challenging environments and presents hybrid methods and models designed to resist noise, improving accuracy and reliability. Finally, the section 3.3 on phase-to-height conversion discusses how ML models help correct errors and recover depth accurately in practical settings, enhancing the calibration methods used in FPP.

3.1. ML for effectiveness improvement in phase demodulation

This subsection discusses a variety of ML techniques that improve the accuracy of phase demodulation. It covers a range of methods that use sophisticated technologies, such as CNNs and transformer-based models. These techniques are designed to solve complex problems like spurious phase signs and irregular-shaped apertures (section 3.1.1). The discussion further delves into fringe pattern analysis (section 3.1.2), and single-shot methodologies (section 3.1.3), showcasing advancements exemplified by methodologies like CDLP, SAPR-DL, and speckle matching networks.

3.1.1. Interferometry in phase demodulation. This subsection explores how ML is applied in interferometry, to improve the effectiveness of measurements. By studying different methods, including CNN and transformer-based models, applied to interferometry, we find ML can improve data interpretation. These techniques increase resistance to noise and adapt to complex measurement conditions, thus enhancing the effectiveness of optical metrology [127–129]. Table 15 shows the pros and potential cons of each method.

Sun *et al* [127] introduced a high-precision, ultra-fast phase demodulation method called RU-Net for optical surface measurements, enabling simultaneous wrapped phase extraction from a single interferogram. The study used a Zygo interferometer to measure two spherical surfaces, capturing several interferograms by adjusting the tilt and defocus to control the shape and density of the fringes. Both the integrated phase-shifting algorithm of the Zygo interferometer and RU-Net were employed to reconstruct the surfaces from these interferograms. The performance of RU-Net was quantitatively assessed by comparing the peak-to-valley and root

Table 15. Section 3.1.1: summary of methodologies for effectiveness improvement in interferometry in phase demodulation.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Sun *et al* [127], 2022	RU-Net for phase demodulation from single interferogram	High accuracy, effective in unstable environments, simultaneous phase demodulation	May require large training datasets	Extension to various interferograms
Li *et al* [128], 2023	I-Net for phase demodulation with focus on Zernike coefficients extraction	Robust to noise, effective for irregular apertures, precise Zernike extraction	Low contrast and uneven fringe	Broader aberration handling, enhanced noise robustness
Kuang *et al* [129], 2024	Swin-ResUnet	Effective segmentation, handles spurious phase sign	Potential model complexity	Wider metrology application, improved segmentation accuracy

mean square (RMS) values of the residual wavefronts derived from the measurements. RU-Net demonstrated a RMSE 0.01λ better than phase-shifting algorithm. These experiment results demonstrate that RU-Net is capable of achieving high precision in the real-time measurement of optical surfaces. The study highlights RU-Net's feasibility and effectiveness in optical metrology applications, addressing challenges in accuracy and robustness that are crucial for advanced metrological tasks.

Following this, Li *et al* [128] introduced a high-precision phase demodulation method called I-Net. This method is especially good at extracting Zernike coefficients from single-frame interferograms, even when those interferograms have irregular-shaped apertures. They conducted an experimental validation of I-Net by comparing its performance with a Fizeau interferometer under varied noise conditions. By training networks with Gaussian and Gamma noises to demodulate interferograms shaped as elliptical, hexagonal, and square apertures, the study demonstrated that network compatibility with the interferometer varied by noise type and aperture shape. For instance, Gaussian noise training yielded an RMS of 0.0131λ for elliptical apertures, while Gamma noise was most effective for hexagonal apertures with an RMS of 0.0096λ. The analysis of Zernike coefficients showed that I-Net's predictions closely matched those of the Fizeau interferometer, affirming its high accuracy. The results showed that this ML approach is not only accurate but also robust, making it highly suitable for measuring optical surfaces that have irregular apertures.

Building on these advancements, Kuang *et al* [129] tackled a challenge: extracting phase information from single interferogram that have closed fringes, particularly focusing on issues with incorrect phase signs. They used a transformer-based architecture called Swin-ResUnet, which has shown an improvement in correcting phase sign errors and better segmentation performance. This improvement is notable compared to older methods like U-Net [83], Swin-Unet [130], and MultiResUnet [131], particularly in handling noise and achieving effective results in both simulations and practical experiments. The team utilised MIoU to assess segmentation accuracy across various wrapped phase images with spurious signs. Swin-ResUnet demonstrated superior precision, particularly in handling complex fringe patterns and high noise levels. For instance, under severe Gaussian noise conditions (SNR of 5 dB), Swin-ResUnet outperformed other models, maintaining segmentation accuracy and robustness, with MIoU values exceeding 90% even when images were substantially corrupted. This robustness is attributed to its self-attention mechanism, which effectively captures global interactions and refines edge detection in phase sign change maps.

The studies reviewed highlight the impact of ML on improving interferometry. By using advanced ML models, researchers have achieved improvements in data accuracy, robustness, and adaptability under different conditions. These advancements not only enhance the ability to obtain precise and reliable measurements from complex data but also broaden the potential uses of optical metrology in areas where traditional methods might be inadequate [127–129].

3.1.2. Fringe pattern analysis in phase demodulation.

The integration of ML into optical metrology has improved fringe pattern analysis, which is essential for precise measurements in various scientific and engineering fields [132]. The shift from using single-frame techniques to ensemble-based approaches in fringe pattern analysis represents an advancement in optical metrology [133]. Table 16 shows the pros and potential cons of each method.

Feng *et al* [132] developed a method utilises ML for fringe pattern analysis in optical metrology. This method enhances the precision of extracting phase information from a single pattern. The effectiveness of this method was shown through experiments, and it could be useful in different techniques for measuring phases. Practical application in optical metrology were demonstrated through a comparative study involving FT, WFT, and a proposed ML-based method. The study calculated the MAE against a reference phase map obtained via a 12-step PS method. Results indicated that FT exhibited the most significant phase distortion with an MAE of 0.20 rad, while WFT showed a slightly lower error of 0.19 rad. In contrast, the ML approach yielded the lowest error at 0.087 rad, showcasing its ability to minimise phase distortion, especially in boundary areas or regions with abrupt depth changes. This

Table 16. Section 3.1.2: summary of methodologies for effectiveness improvement in fringe pattern analysis in phase demodulation.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Feng *et al* [132], 2019	ML with two CNNs	High phase demodulation accuracy	Potential limited generalisation across fringe types	Enhance model generalisation
Feng *et al* [133], 2023	Ensemble ML with multiple DNNs	Greater accuracy, reduced error generalisation	Potential increased computational load	Implement adaptive fusion strategies

method eliminated the need for manual parameter adjustments. Additionally, the 3D reconstructions from unwrapped phase data showed that, unlike the grainy distortions usually seen with FT or the overly smoothed surfaces typical of WFT, the ML method created high-quality reconstructions. These were almost the same as the original models used in the 12-step PS fringe patterns, clearly demonstrating the method's robustness.

Building on this, Feng *et al* [133] improved their research by using a method called ensemble ML to analyses fringe-pattern in optical metrology, which helps make reliable predictions in different situations. They combined the results from multiple DNNs using techniques such as K-fold average and adaptive ensemble strategies, increasing the accuracy and ability to generalise. This method is much better than single-DNN-based methods, such as U-Net [82], MP DNN [132], and Swin-Unet. This study shows the benefits of using a group of models together, called ensemble learning, to improve techniques in optical metrology. These models were trained using a seven-fold average ensemble on three untrained scenarios: statues, an aluminium alloy industrial part, and a plastic desk fan. The ensemble approach outperformed individual models, demonstrating a reduction in MAE across various complex and smooth areas. For instance, the MAE improved from 0.085 rad in initial measurements to 0.061 rad, 0.054 rad and 0.059 rad in the three scenarios, respectively. The study illustrated that while individual DNNs showed varied performance across different scenarios, the ensemble method effectively leveraged their collective strengths, reducing phase errors, particularly around complex depth variations and edges. This method not only improved the accuracy by up to 26% but also showcased enhanced robustness and scalability.

The 2023 [133] paper builds on the 2019 [132] work by introducing ensemble learning, which uses multiple models to overcome the limitations of a single DNN. This approach addresses problems like overfitting and improves the model's ability to perform well across different situations and its robustness. This evolution marks a shift from relying on a single network to using a combined approach with multiple networks, enhancing fringe pattern analysis.

3.1.3. Single-shot methods in phase demodulation. The single-shot methods in optical metrology, particularly FPP, benefit from ML's ability to handle complex data patterns and improve measurement accuracy. These advancements are crucial for applications that require precise 3D surface measurements, such as quality control in manufacturing or dynamic scene analysis [134]. The following comparative analysis explores three studies that use ML to enhance single-shot optical metrology. Each study presents unique approaches and contributions to the optical metrology [134–136]. Table 17 shows the pros and potential cons of each method.

Li *et al* [135] introduced the CDLP, which merges ML with spatial frequency multiplexing to achieve precise and clear single-shot 3D shape measurement. Experiments involved projecting custom-designed composite fringe patterns onto diverse objects, including statues and moving figures, to capture single-shot 3D images. The CDLP approach effectively minimised spectrum aliasing [137] and handled high-frequency shifts, challenges commonly faced with traditional methods [138]. Notably, the method demonstrated high precision in static scenarios, achieving a MAE lower than traditional FT methods. In dynamic scenarios, such as rotating or moving objects, CDLP's single-shot capability proved essential for capturing accurate 3D measurements without the errors typically induced by object motion. These tests showcased CDLP's robustness and adaptability, confirming its suitability for high-resolution, real-time 3D surface imaging.

Expanding on this idea, Xu *et al* [136] tackled the challenge of accurately retrieving absolute phase for isolated objects using single-shot FPP. They introduced a method called SAPR-DL, which can accurately measure the 3D shape of complex objects in one shot, showing potential applications in science and engineering. The method's performance was assessed against ground truth in four scenarios involving discontinuous objects, where it displayed superior phase retrieval capabilities with minimal errors primarily at object edges. The MAE ranged from 0.08 rad to 0.15 rad across these tests, showcasing its precision. In comparison to the Fringe-Depth method, SAPR-DL achieved lower depth errors, with RMSE values better across all tested scenarios (0.77, 0.43, 0.88, and 0.78 respectively for SAPR-DL versus 1.47, 1.02, 0.95, and 1.42 for Fringe-Depth). These results highlight SAPR-DL's robustness and its ability to handle phase and depth ambiguities effectively.

Additionally, Wan *et al* [134] introduced FrANet, a method for single-shot 3D measurement using a DNN with three specialised subnetworks: phase demodulation, phase unwrapping, and refinement. Notably, their two-stage training strategy, starting with unsupervised learning and then fine-tuning with supervised learning, reduced the need for ground truth phase

Table 17. Section 3.1.3: summary of methodologies for effectiveness improvement in single-shot methods in phase demodulation.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Li *et al* [135], 2022	CDLP, ML-based frequency multiplexing coded method	High precision in 3D imaging, suitable for dynamic objects	Potential complexity computational resource requirement	Retrieve robust and unambiguous phases information
Xu *et al* [136], 2023	SAPR-DL method using ML	Precise 3D shape reconstruction with one fringe image	Possible limitations NN training data quality	Improve the ML framework for better generalisation
Wan *et al* [134], 2023	Single-shot 3D measurement by FrANet	High accuracy in 3D reconstruction, effective for dynamic scene measurements	Potential complexity of the network architecture	Enables the accurate 3D shape measurement of moving or vibrating objects

maps. Experimental results from a FPP system showed the method's accuracy in 3D measurements, achieving a RMSE of 0.67 mm. Ablation studies further validate the effectiveness of this approach, highlighting its potential for precise 3D shape measurement in industrial applications, especially for dynamic or vibrating objects.

In summary, incorporating ML into single-shot optical metrology has shown improvements in measurement accuracy. Although each paper introduces a unique approach with its own benefits and potential drawbacks, the overall advancements highlight the impact of ML in optical metrology [134–136]. Future research should aim to overcome the identified challenges, such as data dependency and generalisation issues, to fully utilise ML's potential in enhancing single-shot optical metrology techniques for a wider range of challenging applications.

3.1.4. Discussion about section 3.1: ML for effectiveness improvement in phase demodulation. In conclusion, this review highlights the progress made in applying ML to phase demodulation. It presents a variety of methods that improve measurement accuracy. The studies discussed show a clear trend: using ML not only overcomes traditional challenges in phase demodulation but also opens up new possibilities and methods. Future research should aim to improve these ML techniques, explore how they can be scaled up, and combine them further with new optical metrology technologies. The ongoing collaboration between ML and optical metrology is likely to lead to new opportunities, making optical metrology more effective and wide-ranging.

3.2. ML for effectiveness improvement in phase unwrapping

This subsection examines the multiple applications of ML in the complex process of phase unwrapping, addressing different scenarios within interferometry (section 3.2.1), InSAR (section 3.2.2), FPP (section 3.2.3), and challenging noisy environments (section 3.2.4). A synthesis of hybrid methodologies, advanced ML frameworks, and anti-noise models collectively drives the field forward, contributing to improvements in phase unwrapping across various contexts of optical metrology.

3.2.1. Interferometry in phase unwrapping. This literature review introduced some studies that use ML to improve the accuracy [139] of interferometric measurements. These studies highlight a shift towards using ML to solve issues in phase unwrapping and quality map creation, thereby increasing the precision and reliability [140, 141] of optical metrology. Table 18 shows the pros and potential cons of each method.

Zhao *et al* [140] addressed the challenge of phase unwrapping in optical phase measurements under heavy noise conditions. The proposed method combined Zernike polynomial fitting with a Swin-Transformer network, treating phase unwrapping as a regression task. This method demonstrated robustness to noise, offering potential applications in quantitative phase measurement, particularly in scenarios characterised by severe noise like speckle interferometry. The proposed method consistently outperformed traditional methods, with RMSE values substantially lower, such as 0.0407 rad and 0.0627 rad in typical scenarios, and even lower in noise-intensive tests. Comparative analyses against methods like D-Net and DZPF under varied noise levels further highlighted its superior performance, with the model maintaining low error rates (as low as 0.0153 rad) where others failed, particularly in high-noise environments.

Building on this, He *et al* [142] introduced UN-PUNet, a CNN designed for phase unwrapping from single wrapped phase patterns with uneven grayscale and noise in electronic speckle pattern interferometry (ESPI). Tested against 1224 uneven noisy phase patterns, UN-PUNet outperformed competing methods (DLPU-Net [144], VUR-Net [145], and PU-M-Net [146]) across many metrics including AU, PSNR, SSIM, and CC, indicating its enhanced accuracy, noise reduction, and structural preservation capabilities. Notably, UN-PUNet achieved the lowest MSE, highlighting its precision in phase retrieval.

Furthermore, Li *et al* [141] introduced a three-wavelength phase unwrapping approach using a MW-Net to predict the

Table 18. Section 3.2.1: summary of methodologies for effectiveness improvement in interferometry in phase unwrapping.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Zhao *et al* [140], 2023	ML-based phase unwrapping	High accuracy and performance with different types of noise and fringe shapes	May struggle with extremely noisy data	Improve noise handling and robustness to different data types
He *et al* [142], 2023	UN-PUNet for phase unwrapping	Improved feature extraction and multi-scale information fusion, effective on uneven and noisy wrapped patterns	Specific performance on very high-density noise patterns	Eliminating speckle noise, and addressing uneven gray scale
Li *et al* [141], 2023	MW-Net for multi-wavelength phase unwrapping	Increases measurement range without additional noise, effective for complex samples	Performance may degrade with extremely low SNR images	Enhance robustness and extend applicability
Han *et al* [143], 2023	NN-based phase quality map generation	Improves path-based and network-based phase unwrapping algorithms	May require big data for training and validation	Identify the residuals and generate a reliable gradient quality map
Jiaying and Xianming [139], 2023	ML-based CDIF phase unwrapping	Combines ML with PG estimation for robust results	Possible time-consuming optimal path search in the entire interferogram	Optimise path-searching algorithms to improve accuracy

illumination wavelength from a single-wavelength interferogram. In simulations, the network accurately predicted different wavelength interferograms from a single-wavelength input, closely matching the ground truth with minimal error, as evidenced by a RMSE of 0.0407 rad. This accuracy was maintained across various experimental setups, including complex biological samples like Jurkat cells, where traditional methods struggled with noise and inaccuracies. Particularly noteworthy is the network's ability to extend the measurement range effectively under single-wavelength illumination, showcasing an improved SNR and precise height distribution in complex samples.

Subsequently, Han *et al* [143] focused on the generation of a quality map for phase unwrapping in interferometric signal processing. It introduced a method based on CNNs to create quality maps, which used in path-based and network-based phase unwrapping algorithms, outperformed BUT method [147], PC, PV, PG, SNAPHU [148], DLPU-Net [144], PhaseNet 2.0 [149], QGPU [150] and MCF [151]. For example, the method was validated using TerraSAR-X/TanDEM-X data for a 768 $\times$ 768 pixel interferogram over Ningxia, China, challenging due to its dramatically varying terrain. The proposed method demonstrated the lowest normalised NRMSE of 0.0223, outperforming conventional methods like SNAPHU and other ML approaches like PhaseNet2.0 and DLPU.

Finally, Jiaying and Xianming [139] introduced a ML method called CDIF for phase unwrapping (DLCDIFPU). They combined this method with a ML-based region segmentation model to make phase unwrapping more accurate. Experimental results on synthetic and measured data showed the robustness of this method compared to commonly used algorithms, such as Goldstein's BUT [152], the QGPU [150, 152, 153], the ILS [154], the improved unscented UKFPU [155].

The studies discussed how ML is making advancements in interferometry within optical metrology. These approaches provide solutions to challenges like phase unwrapping and quality assessment. These improvements not only increase the accuracy [139] of measurements but also open up new possibilities for future research and applications in this area, establishing ML as a component in the development of optical metrology.

3.2.2. Interferometric InSAR in phase unwrapping. These studies demonstrate how ML improves the accuracy of InSAR phase unwrapping processes [156–159]. They focus on improvements in data interpretation, reduction in error rates, and better performance across various terrains and conditions. Table 19 shows the pros and potential cons of each method.

Vijay *et al* [156] presented a two-stage ML framework inspired by U-Net for InSAR phase unwrapping and denoising. The proposed method demonstrated superior noise immunity and accuracy, with consistently lower RMSE and UFR, and higher SSIM values. The proposed U-Net based model effectively maintained correct phase boundaries and minimised noise distortions, producing outputs with fewer errors and higher quality, even in challenging scenarios. This robust performance, particularly in handling noise and maintaining accurate unwrap boundaries, underscores the proposed method's enhanced capability and scalability in practical optical metrology settings

Table 19. Section 3.2.2: summary of methodologies for effectiveness improvement in interferometric InSAR in phase unwrapping.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Vijay *et al* [156], 2023	U-Net for denoising and unwrapping	Integrates denoising and unwrapping, reducing error propagation	May reduced performance in extremely high-coherence regions	Better anti-noise behaviour
Zhang *et al* [157], 2023	Pu-pix2pix for one-step unwrapping	Handles varied noise conditions well	May require substantial data diversity for better generalisation	Broaden dataset variety and enhance network to deal with SAR phase unwrapping
Yang *et al* [159], 2023	Deep-learning-based mask-cut method	Accurate MC deployment without quality map guidance	May struggle with dense fringe wrapped phases	Improve the phase unwrapping success ratio
Chen *et al* [158], 2023	U-GauNet for InSAR phase unwrapping	Handles error gradient distribution effectively	May not perform well in extremely low-coherence areas	Enhance training with diverse datasets

Zhang *et al* [157] presented a robust InSAR phase unwrapping method that used an improved pix2pix [160] network model, called pu-pix2pix. The proposed method integrated the concept of quality map guidance [161] and showed superior unwrapping accuracy and robustness to phase noise when compared to other InSAR phase unwrapping algorithms, such as QGPU [150, 152, 153], LS [154], MCF [151], U-Net [162, 163], and pix2pix. Quantitative evaluations revealed the lowest RMSE for pu-pix2pix, substantially improving other methods. In addition, its computational efficiency was highlighted, with faster processing times compared to traditional wrapping methods.

Furthermore, Yang *et al* [159] introduced MCNet-PU, a ML method for mask-cuts deployment [164], which is essential for phase unwrapping in InSAR. MCNet-PU improved the phase unwrapping success ratio by about 4%–15%, offering an accurate approach for InSAR data processing. The method's robustness, accuracy, and scalability were quantitatively assessed using metrics such as PA, IoU, and RMSE across varied noise conditions. Initial experiments demonstrated that MCNet-PU outperformed other methods like the quality guide, LS, and both older and contemporary NN models. Specifically, in high-noise scenarios, MCNet-PU maintained lower RMSE values and demonstrated superior unwrapping accuracy, with minimal phase information loss even in complex terrain conditions.

Subsequently, Chen *et al* [158] introduced a two-stage InSAR phase unwrapping method using the U-GauNet and L1-norm, where the first stage estimates the phase ambiguity gradient with a loss function related to error distribution, and the second stage minimised the difference between the estimated and true ambiguity gradient. U-GauNet was assessed using simulated data derived from the SRTM DEM, with coherence values ranging from 0.5 to 1. The method's stability and accuracy were demonstrated by its consistently low RMSE, particularly when the coherence dropped to 0.5, where it outperforms traditional 2D phase unwrapping methods including branch cuts (BCs) [165], Quality Map [166], MCF [151], and LS [167], but it may face challenges when the coherence of the simulated data is very low.

These ML-based methods have proven effective in handling complex and noisy data environments [156, 157], showing improvements over traditional phase unwrapping techniques [158, 159]. Future developments are expected to further utilise the adaptability and learning capabilities of NNs, potentially incorporating knowledge [156] from related fields such as optical physics, signal processing, and computational intelligence.

3.2.3. *FPP in phase unwrapping.*

Recent advancements in FPP have been enhanced by the integration of ML [168–172]. These methods aim to overcome challenges typically found in traditional FPP, such as sensitivity to noise, error buildup in phase unwrapping, and difficulties with complex surface geometries. The ability of ML to learn from data improves the accuracy and robustness of phase recovery, offering a possible direction for refining FPP methods. By recognising complex patterns and relationships within the data, these models enable better phase unwrapping and surface reconstruction, even in difficult conditions. Table 20 shows the pros and potential cons of each method.

Luo *et al* [168] addressed the challenge of robust spatial phase unwrapping in complex scenes, focusing on the FPP system. It proposed a hybrid method that combines ML-enabled invalid-point removal with traditional path-following. Experiment result shows its ability to handle 514 simple phase maps without any failures and maintaining a lower number of failures across 1137 phase maps with motion blur or low reflectivity, and 890 phase maps with phase discontinuities, demonstrating better robustness than traditional quality-guided methods including MODU-sort [173], FSPU [174] and WFT-sort [96, 97], and better interpretability than end-to-end ML approach HiPhase [175].

Subsequently, Zhu *et al* [169] presented a single-input triple-output NN structure with a physical prior to improve the accuracy of deep-learning-based unwrapped phase methods in

Table 20. Section 3.2.3: summary of methodologies for effectiveness improvement in FPP in phase unwrapping.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Luo *et al* [168], 2023	ML enhanced FPP	Improves phase unwrapping accuracy, handles noise better	Requires extensive training data	Enhanced robustness, interoperability, and generality
Zhu *et al* [169], 2023	Single-input triple-output NN with physicalprior	Enhanced resolution, better surface detail capture	Complexity may increase with additional frequencies	Structure could be extended to other NN models in phase unwrapping
Wang *et al* [170], 2023	VRNet for phase unwrapping	Accurate and single-frequency phase unwrapping without extra cameras	May be less accurate compared to multi-shot methods	Improve accuracy through advanced network architectures
Huang *et al* [171], 2023	Pixel-wise ML for FPP	High precision in phase unwrapping at a pixel level	High computational load	Exhibit superb resistance to severe noise
Guo *et al* [172], 2023	Unifying the ML framework for TPU	Generalises across different TPU methods, improved noise resistance	Complex training process	Potential for robust and accurate phase unwrapping

FPP. It has been shown that the proposed U-Net based network enhances the accuracy of unwrapped phase prediction. With a dataset comprising 640 $\times$ 480 pixel fringe patterns, the proposed model was trained, validated, and tested in an 8:1:1 ratio, leveraging stochastic gradient descent with a momentum of 0.9 and a polynomial decay learning rate. Performance evaluations highlighted the method's enhanced capability to accurately predict unwrapped phases.

Meanwhile, Wang *et al* [170] introduced a network with the encoder-decoder structure for phase unwrapping (VRNet), a CNN for single-frequency and accurate phase unwrapping in FPP, eliminating the need for additional cameras. In comparative tests, VRNet consistently achieved the lowest MSE and the highest SSIM and absolute unwrapping scores, surpassing 0.99, indicating an almost perfect match with reference data. VRNet is capable of achieving high-accuracy phase unwrapping even in complex real scenes. It can process data with resolutions greater than the training data, making it an advancement in FPP applications.

Additionally, Huang *et al* [171] introduced a ML-based approach for pixel-wise phase unwrapping in FPP, which was crucial for high-precision optical metrology. The method maintained high accuracy and low MSE even when noise levels were increased significantly, showcasing its robustness compared to traditional methods like the three-wavelength heterodyne method, which displayed substantial error rates under similar conditions. Further, the DL-PWPU was tested against large depth discontinuities, a common challenge in phase unwrapping, where it consistently outperformed other methods by accurately predicting fringe orders even at depth discontinuities.

Finally, Guo *et al* [172] addressed TPU for FPP, which is important for achieving unambiguous phase recovery in optical metrology. The proposed approach used ML to create a unified framework for TPU across different TPU algorithms, enhancing phase unwrapping reliability while mitigating the impact of noise. The experimental setup comprised a high-contrast camera and a DLP projector, testing fringe patterns at frequencies from 1 to 64, which demonstrated FOA-Net's adaptability across a spectrum of measurement scenarios. The network was implemented on a powerful computing platform, optimising its structure over 200 training cycles, leading to a prediction rate that outpaced traditional methods by 20%.

The integration of ML into FPP marks an improvement in optical metrology, enhancing the method's ability to provide precise and reliable measurements [170, 172]. A comparative analysis of recent studies shows a trend toward more sophisticated, data-driven approaches that overcome the limitations of traditional algorithms. This provides a framework for addressing various metrological challenges [168]. As ML algorithms continue to develop, their use in FPP is expected to further enhance the accuracy and usefulness of optical metrology.

3.2.4. Noisy environments in phase unwrapping. The use of ML for phase unwrapping in noisy environments, marks an improvement in measurement accuracy [176] and robustness [177, 178]. Recent studies have used various ML frameworks to address the challenges caused by noise and other distorting factors, showing advancements over traditional methods. These approaches utilise the abilities of NN to learn complex patterns and relationships, enabling more precise and reliable phase unwrapping. The incorporation of ML not only enhances the effectiveness of optical metrology under challenging conditions but also creates new opportunities for research and application in this field. Table 21 shows the pros and potential cons of each method.

Chen *et al* [179] introduced the nested U^2-Net for solving a common problem in optical metrology called 2D phase unwrapping. Their study tested how well different

Table 21. Section 3.2.4: summary of methodologies for effectiveness improvement in noisy environments in phase unwrapping.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Chen *et al* [179], 2023	U^2-Net with U-shaped structure	Deep network without increasing too many parameters, performs well in noise environments	May require big data for training to achieve generalisation	Potential for a wide applicability with respect to PU
Gontarz *et al* [177], 2023	CNN based pipeline	Pipeline makes possible the phase unwrapping of highly irregular, noisy, and complex experimental phases captured in HT	May requires extensive training data and computational resources	Incorporation of ML to enhance robustness and adaptability in complex conditions
Li and Xie [178], 2023	SCAPU method	Demonstrates robustness, effective in PU for interferograms	May need compare more methods	SCAPU method can effectively suppress phase noise from noisy interferograms
Zhu *et al* [176], 2022	Hformer model	Combines advantages of CNN and transformer, enhances global dependency for fringe order prediction	May requires extensive training data and computational resources	Extended to two frames wrapped phase in stereo-based PU

advanced network models perform in noisy conditions The real-sample tests involved 421 dynamic candle flame images with complex geometries, where U^2-Net and its variant U^2-Netp showed significant resilience, maintaining high structural integrity and unwrapping accuracy. Quantitative evaluations using MSE, PSNR, and SSIM metrics further underscored U^2-Net's enhanced performance, particularly in maintaining high SSIM values close to 1. The results showed that the U^2-Net was effective at dealing with noise, maintaining structure, and working well in various situations. This performance was better compared to other models like U-Net [82, 180], DLPU-Net [144], VUR-Net [145], and PU-GAN [181], especially when facing real-world scattered noise.

On a related note, Gontarz *et al* [177] focused on improving phase unwrapping in HT, a technique that faces issues with high noise and irregular phase images. They proposed a method using a CNN to make the process more robust, reliable, and automated. This method involves steps for reducing noise and unwrapping the phase, and it has shown effective results in managing the complex and noisy images typically produced by HT. The method effectively handles the complexities of real-world data, indicated by consistent phase details post-denoising and accurate unwrapping even in the absence of noise-free GT images. Although performance metrics such as MSE, RMSE, and SSIM show degradation post-processing due to noise removal steps, the overall integrity and visibility of structures within measured specimens are maintained.

Additionally, Li and Xie [178] developed introduced the SCAPU for phase unwrapping, using a ML network. This method works well on interferograms, even with different levels of noise. The results from their experiments are impressive. Because SCAPU performs better than other known methods QGPU [150] and ILS [154] method, especially in terms of robustness. This marks an advancement in phase unwrapping technology. Lastly, Zhu *et al* [176] explored the complex topic of phase unwrapping in 3D fringe projection using ML. They pointed out the limitations of traditional methods, like CNNs, especially their difficulty in correctly identifying the order of fringes in wrapped phase patterns, which depend on continuity and overall characteristics. They introduced a new model called Hformer, which combines CNNs with transformer technology. This model has proven to be more effective in identifying fringe order than older CNN models such as U-Net and PhaseNet 2.0 [149]. This method offers a way to use ML for phase unwrapping in 3D fringe projection.

The integration of ML into optical metrology, particularly for phase unwrapping in noisy environments, has shown advancements. These new methods improve upon traditional techniques by offering better accuracy [176], noise resilience, and adaptability. Future research should continue to develop these approaches, focusing on refining the models, enhancing their real-world applicability, and deepening our understanding of the mechanisms that drive these improvements.

3.2.5. Discussion about section 3.2: ML for effectiveness improvement in phase unwrapping. In conclusion, the assessment of various ML applications in phase unwrapping highlights a trend towards increased accuracy [139, 157, 159, 169–172, 176], robustness [139–141, 168, 172, 177, 178], and adaptability. ML effectively addresses challenges like noise and data complexity [176–179]. Future research should focus on fully harnessing the potential of ML by exploring architectures and real-world applications to further enhance the effectiveness of optical metrology.

Table 22. Section 3.3: summary of methodologies for effectiveness improvement in phase-to-height.

Author	Method	Pros	Potential cons	Potential effectiveness improvement
Feng *et al* [182], 2021	Review of calibration methods in FPP	Comprehensive insights, covers a range of models	Does not focus on a single innovative solution	Comparative overview on the accuracy and the implementation details of calibration
Li and Li [183], 2023	TPDNet: texture-guided phase to depth networks	Repairs shadow-induced errors	Performance affected by ambient light	Enhance model robustness to lighting conditions

3.3. ML for effectiveness improvement in phase-to-height conversion

This subsection discusses two papers to the phase-to-height conversion: a ML model for error correction in review of calibration techniques [182] and shadow-affected measurements [183]. It explores a spectrum of methodologies, including comprehensive calibration techniques in FPP, the integration of a phase-to-height conversion ML model for mitigating shadow-induced errors, and the introduction of a practical depth recovery approach founded on pixel cross-ratio invariance, all aimed at augmenting the precision of phase-to-height conversion. Table 22 shows the pros and potential cons of each method.

Feng *et al* [182] provided a review that includes comparative experiments and discussions. This review helps in evaluating different calibration methods. Crucially, the insights gained from this analysis are useful for choosing the right methods for phase-to-height conversion. Subsequently, Li and Li [183] introduced a TPDNet. This model is designed to correct errors caused by shadows in FPP used for 3D shape reconstruction. Notably, the model uses texture images to help correct these shadow-related errors [184], showing encouraging results in improving the accuracy of FPP, especially in difficult situations where shadows are present. Utilising the texture image and unwrapped phase map, the pre-trained TPDNet successfully predicted the depth map and 3D geometry. For areas not covered by shadows, the model achieved an RMSE of 1.5031 mm, indicating high accuracy in depth prediction. The model effectively filled holes in the 3D geometry, though minor discontinuities were noted in some shadowed regions, highlighting the model's capability to handle shadow-induced discrepancies effectively.

Recent advancements in optical metrology have used ML and new computational methods to overcome challenges in phase-to-height conversion. This subsection examines two contributions to the field: error correction in shadow-affected measurements [183] and a review of calibration techniques [182].

4. Conclusion

This literature review highlights the impact of ML on optical metrology, revealing improvements in both efficiency and effectiveness across various measurement processes. ML has been applied to enhance data generation, sampling strategies, and to optimise processes like phase demodulation, phase unwrapping, and phase-to-height conversion, increasing the speed and accuracy of optical metrology. The review also details progress in end-to-end 3D reconstruction, pointing to future opportunities for further advancements and innovations in optical metrology. Parallel computing has boosted these developments by speeding up computations, enabling real-time processing and analysis that were not possible before.

Some studies utilise CNNs for better phase demodulation and unwrapping, while others use ML frameworks for complete 3D reconstruction. The level of ML integration varies across these studies, from enhancing traditional techniques for noise reduction and data interpretation to improving measurement processes. These successes point to a future where combining domain-specific knowledge with ML advancements could lead to unparalleled accuracy and reliability in measurements. Overall, the insights from these studies suggest that optical metrology is evolving towards a more data-driven, automated future, increasingly reliant on interdisciplinary collaborations that merge ML and optical metrology to develop solutions that improve traditional methods.

4.1. Efficiency improvement through ML

Improving efficiency by overcoming challenges related to measurement speed, data bottlenecks, and time-intensive techniques. ML has streamlined data generation, refined sampling strategies, and increased overall computational speed [11–15]. The use of parallel computing, particularly through GPUs and FPGAs, enabling real-time processing for optical metrology. These improvements not only save time and resources but also broaden the potential applications of optical metrology. The move towards end-to-end ML solutions represents a shift from using ML in isolated tasks to a more integrated approach.

4.2. Effectiveness improvement through ML

ML has impacted the effectiveness of optical metrology, especially in tasks like phase demodulation, unwrapping, and phase-to-height conversion. Sophisticated ML algorithms have increased the accuracy and robustness of these processes [129, 140, 183], addressing issues related to noise, data complexity, and environmental variations. This has led to more reliable measurements, supporting applications in fields such as precision engineering and manufacturing.

4.3. Challenges

ML models, known as 'black boxes', might not always follow the physical laws that traditional models do. This could lead to unrealistic results, particularly when faced with data or conditions not covered by the training data. Moreover, the effectiveness of ML models is heavily dependent on the quality and variety of their training data. In real-world situations, the rarity and complexity of obtaining suitable data in optical metrology can hinder the models' robustness and reliability.

The opaque nature of NNs poses risks to the traceability and repeatability of measurements in metrology. For instance, when a noisy fringe pattern is processed by an ML model to produce a clear image, it is often unclear how the model reached that conclusion. Understanding these processes is crucial for ensuring that measurements can be repeated and errors can be traced. The use of ML in optical metrology is challenging without clear explanations for its decisions or the ability to adjust the model based on its performance.

4.4. Future direction

Transition from physics-based model to data-driven model approaches: The shift towards a data-driven paradigm, facilitated by ML, improves how we handle the intricacies of optical metrology. Unlike traditional models that rely on predefined physical models and extensive prior knowledge, ML utilises a learning-based representation where the algorithm is directly learned from experimental data. ML does not depend on prior understanding of the physical model. The data-driven model is robust against varying experimental conditions provided the training dataset is representative and diverse. This ensures the model captures the true characteristics of the system more accurately and extensively, offering better outcomes over conventional methods.

Adopting end-to-end learning: By surveying ML's end-to-end learning capabilities, we could integrate the entire measurement process into a single cohesive model. This contrasts with the traditional divide-and-conquer approaches and allows for simultaneous processing of interrelated tasks. This integration not only simplifies the computational framework but also enhances performance by leveraging shared features and learning direct mappings from raw image data to desired sample parameters. This holistic approach mitigates the risk of error propagation inherent in multi-step processes.

There is no unified measurement standard for the interpretability of ML model, making it difficult to quantitatively analysis compare the ML model. Therefore, designing a comprehensive interpretable evaluation system is one of the solutions for reliability of ML applications in real-world.

In conclusion, as optical metrology progresses towards a more automated and data-driven future, the interplay between ML innovations and domain-specific knowledge will be pivotal in overcoming current limitations and unlocking improved measurement capabilities. The ongoing development of interpretable, robust ML models that can adapt to diverse and challenging environments will play an important role in this evolution.

Data availability statement

No new data were created or analysed in this study.

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Appendix. Summary of ML algorithms

This is a supplementary section where we list the major ML algorithms, explaining their strengths, weaknesses, and applications in optical metrology techniques in table 23.

Table 23. Section appendix: ML method in optical metrology.

ML Method	Pros	Potential cons	Application or suitability for optical metrology
μDLP [71], 2019	Capable of high-quality 3D reconstructions from a small number of images.	Dependent on the quality and variation of input fringe patterns.	Suitable for capturing dynamic and transient scenes in optical metrology, where high frame rates and detailed structure capture are necessary.
PI-FPA [72], 2023	Low computational cost compared to traditional end-to-end networks. Integrates physics-priors.	Integration complexity might increase with the need for fine-tuning in different applications.	Ideal for high-speed 3D imaging and modelling of complex structures, suitable for environments where traditional data collection is challenging.
DYnet++ [73], 2023	Efficient in retrieving phase information from low-reflectivity surfaces.	Dependency on initial training from deformable mirrors may limit generalisation without fine-tuning.	Ideal for industrial applications requiring rapid and precise measurement of complex or low-reflectivity surfaces, such as in real-time manufacturing processes.
DL-TPU [74], 2019	Suitable for high-speed 3D surface imaging and dynamic measurements.	Dependency on extensive training data for high performance.	Applicable to a range of optical metrology techniques beyond FPP, such as stereo vision and digital image correlation.
RCNN [78], 2024	Reduces the number of required fringe patterns, increasing measurement speed and reducing complexity.	Requires additional imaging tools for complex surface materials to enhance performance.	Ideal for SL 3D imaging in industrial and scientific applications where quick and reliable surface measurements are crucial.
PCTNet [81], 2023	Capable of handling complex scenes by preserving both global structure and local details.	Complexity of the network architecture might require significant computational resources.	Suited for SL depth estimation tasks, effective in fringe and speckle projection 3D measurements.
DCAHINet [85], 2023	Superior performance in feature extraction due to deformable convolutions.	May require extensive training data to optimise performance across different devices.	Well-suited for dynamic 3D reconstruction tasks in single-shot FPP, effective in noisy and complex measurement environments.
LiteF2DNet [86], 2023	Efficient in terms of memory and processing time, suitable for real-time applications.	Potential limitations in handling extremely complex or highly reflective surfaces due to synthetic training.	Primarily designed for dynamic and real-time 3D reconstruction tasks in optical metrology.
CF3DNet [87], 2023	Unique end-to-end mapping of phase deformations enables reconstruction of discontinuous object profiles.	Might struggle with real-world challenges like reflectivity differences and shadow effects without further adaptation.	Suitable for cost-effective fringe projection systems in dynamic scenarios where discontinuities and complex shapes are involved.
MPCAM [90], 2023	Utilises synthetic training to enhance model robustness and generalisation without extensive real data collection.	Limited by the resolution of input images, potentially affecting applications requiring high-detail analysis.	Optimal for environments where traditional optical systems struggle due to DOF and SNR trade-offs, offering a cost-effective solution for dynamic and complex scene reconstruction.
CUE-NET [88], 2023	Enhances local and global feature extraction through deformable convolutions and attention mechanisms.	Potential limitations in adapting to highly variable hardware setups without specific customisation.	Ideal for dynamic 3D reconstruction in complex scenes, particularly where noise and discontinuities challenge traditional FPP methods.
MIMONet [102], 2021	Simplifies the 3D reconstruction process by eliminating camera calibration and triangulation.	May less effective for conventional high-frequency fringe projection in industrial applications.	Suitable for dynamic 3D shape reconstruction in complex scenes, benefiting machine vision and medical imaging.

(Continued.)

Table 23. (Continued.)

SSMNet [89], 2024	Uses instance normalisation for style migration and robust cross-domain capability.	May limited by computational resources and architecture constraints, affecting broader applicability.	Suitable for high-precision binocular 3D reconstruction, particularly in dynamic and small-scale industrial environments.
RU-Net [127], 2022	Better gradient flow for NNs. Scalable depth without performance loss.	Potential for overfitting in scenarios with limited data.	High-resolution image analysis. 3D reconstruction from 2D images.
I-Net [128], 2023	Multi-scale processing and enhanced convergence from diverse convolutional kernels.	Potential high computational demand.	Ideal for interferogram analysis and Zernike coefficient estimation in optical metrology.
Swin-ResUnet [129],2024	Enhanced accuracy in phase unwrapping through refinement processes.	Requires sophisticated processing for phase refinement, increasing computational load.	Primarily used for image segmentation and phase unwrapping in optical metrology.
CDLP [135], 2022	Utilises high-quality datasets for training, including spatial frequency multiplexed fringe encoding.	Dependency on high-quality data for effective training.	Suitable for dynamic and transient 3D surface profiling in optical metrology.
SAPR-DL [136], 2023	Simplifies traditional phase retrieval steps, incorporating them into a deep learning framework.	May require high computational resources due to the complexity of processing multiple frequencies in a single capture.	Ideal for applications that require rapid and precise 3D shape measurements of discontinuous and isolated objects.
FrANet [134], 2023	Reduces the need for extensive ground truth data through a two-stage training strategy.	Complex network structure may demand higher computational resources and more sophisticated tuning.	Suitable for optical metrology settings that require rapid and precise 3D imaging capabilities.
UN-PUNet [142], 2023	Skip connections enhance the flow of information, improving accuracy and robustness.	Potentially high computational demand due to complex structure.	Suitable for applications involving electronic speckle pattern interferometry.
MW-Net [141], 2023	Avoids noise amplification common in multi-wavelength systems.	Dependency on highly accurate training data to achieve optimal performance.	Suitable for optical metrology, that phase imaging where high accuracy and extended measurement ranges are required.
DLCDIFPU [139], 2023	Enhances phase unwrapping accuracy with ML-based region segmentation.	May struggle with extremely low SNR wrapped phase images, limiting its application in poor quality data environments.	Suitable for environments where advanced phase unwrapping is critical.
Pu-pix2pix [157], 2023	Utilises ASPP module to replace traditional convolution down-sampling, improving feature extraction.	The unchanged discriminator may limit adaptability to varied noise levels and image quality.	Suitable for applications requiring accurate phase reconstruction from complex interferograms.
MCNet-PU [159], 2023	Simplified network architecture speeds up training and operation, suitable for binary classification tasks in phase unwrapping.	Performance may dependent on the quality of training data and initial filter settings.	Suited for InSAR applications requiring binary classification of phase unwrapping elements.
U-GauNet [158], 2023	Enhances category pixel localisation through the global attention up sampling module.	May struggle with very high-resolution detail recovery due to the focus on category classification over spatial localisation.	Ideal for optical metrology tasks requiring high accuracy in phase ambiguity resolution.
VRNet [170], 2023	Capable of processing data at higher resolutions than those used in training, demonstrating flexibility and scalability.	Potential overfitting to training data types may occur if not adequately managed.	Suitable for applications demanding accurate phase analysis and reconstruction without the complexity of additional hardware.
DL-PWPU [171], 2023	Enhances accuracy by aligning fringe order boundaries with phase discontinuities, crucial for reducing unwrapping errors.	Potential challenges in handling noisy or incomplete phase data without sophisticated pre-processing.	Well-suited for environments where phase continuity and accurate boundary detection are critical.

(Continued.)

Table 23. (Continued.)

ML Method	Pros	Potential cons	Application or suitability for optical metrology
FOA-Net [172], 2023	Uses residual connections to enhance detail feature extraction and integrate encoder-decoder features effectively.	May require substantial computational resources for training due to complex architecture.	Highly suitable for applications that require accurate fringe order estimation and phase unwrapping.
U^2-Net [179], 2023	Effective in noise management and maintaining structural integrity in phase unwrapping.	Potentially high computational complexity due to multiple stages and depth supervision.	Suitable for 2D phase unwrapping in optical metrology, where maintaining detail and handling noise are crucial.
SCAPU [178], 2023	Robust to various interferogram complexities and noise levels.	Potentially high computational requirements due to deep and complex network architecture.	Suitable for complex and noisy interferogram data in optical metrology.
Hformer model [176], 2022	Improved feature pyramid network merges multiscale features, enhancing the accuracy of fringe order predictions.	The hybrid nature requires careful tuning of both CNN and transformer components to optimise performance.	Suitable for applications where accurate fringe order determination is crucial.
TPDNet [183], 2023	Enhances depth map predictions by integrating texture images and phase maps.	May depend on the quality of texture information and phase maps.	Suitable for optical metrology where shadow-induced errors and depth estimation are critical.

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