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Integration of Machine Learning and Digital Image Colorimetry in Green Synthesis Nanoparticle Logam: A Systematic Review

Integrasi *Machine Learning* dan Citra Digital Kolorimetri dalam Green Synthesis Nanopartikel Logam : Tinjuan Sistematis

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ABSTRACT

Machine Learning (ML) integrated with Digital Image Colorimetry (DIC) has emerged as a low-cost and portable analytical approach for real-time characterization of green-synthesized metal nanoparticles. While UV–Vis spectroscopy remains the conventional method for monitoring nanoparticle formation, its limitations in cost, portability, and early-stage detection warrant alternative solutions. This systematic review evaluates the performance, reliability, and methodological trends of ML-DIC in predicting key nanoparticle parameters, including particle size, concentration, and surface plasmon resonance (SPR) peak, using PRISMA 2020 guidelines. Literature searches in Scopus, Web of Science, and ScienceDirect (2018–2025) identified 465 articles, with 10 meeting inclusion criteria. Extracted features included ML algorithms, color space representation, plant extracts, nanoparticle type, and evaluation metrics. Findings indicate that deep learning models (CNN, LSTM) combined with HSV or Lab color spaces achieve the highest accuracy ($R^2 \geq 0.95$), outperforming classical models in capturing non-linear relationships. ML-DIC demonstrates strong correlation with UV-Vis results while providing advantages of portability, rapid analysis, and cost efficiency. Challenges remain in standardizing illumination, dataset availability, and cross-lab generalization. Future work should focus on open datasets, color calibration protocols, transfer learning, and IoT-based portable sensing systems.

Keywords: *Machine Learning, Digital Image Colorimetry, Green synthesis, Metal nanoparticles, Optical characterization*

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1. INTRODUCTION

Rapid advancements in artificial intelligence and image analysis have transformed how materials are characterized, including in the monitoring of nanoparticle formation. Although the green synthesis of metal nanoparticles using plant extracts serves as the practical context for this study, the primary focus is not on the chemical aspects but rather on how machine learning (ML) algorithms can learn non-linear color change patterns from digital images. Therefore, this review is positioned as an AI-focused systematic review that evaluates the

performance, accuracy, and generalization of various ML models in Digital Image Colorimetry (DIC).

In the green synthesis process, plant extracts continue to function as bioreducing agents and stabilizers, but the color changes that occur during the reaction serve as a rich source of data for ML algorithms. The main challenge is predicting critical parameters such as particle size, concentration, and the position of the surface plasmon resonance (SPR) peak in real-time, which is traditionally done using UV–Vis spectroscopy (Sundararajan et al., 2019). Although UV–Vis is a well-established standard, the technique has limitations in terms of cost, the need for laboratory instruments, and its sensitivity to the early stages of nanoparticle formation (Chen et al., 2022).

Digital Image Colorimetry (DIC) offers a cost-effective, portable, and image-based alternative approach. However, conventional color analysis still struggles to capture nonlinear patterns influenced by the phytochemicals in extracts, metal reduction dynamics, and variations in illumination (Rahman et al., 2018). This is where Machine Learning plays a crucial role. The integration of ML with DIC enables the modeling of complex relationships between color features (RGB, HSV, Lab) and nanoparticle optical parameters, with algorithms such as SVM, Random Forest, Artificial Neural Networks, CNN, and LSTM demonstrating varying performance (Nguyen et al., 2021). These performance variations are influenced more by dataset quality, algorithm selection, and image preprocessing strategies than by the chemical effects themselves. Although ML–DIC studies are advancing rapidly, there has been no systematic review that specifically compares model reliability, accuracy, efficiency, dynamic sensitivity, and cross-device generalization. More importantly, to the best of the authors' knowledge, no previous systematic review has simultaneously combined three aspects: (1) a comparison of ML algorithm performance (LR, RF, SVR, CNN, LSTM), (2) a comparative analysis of color spaces (RGB, HSV, Lab) regarding prediction accuracy, and (3) the ability of ML–DIC to detect the temporal dynamics of synthesis encompassing the nucleation–growth–aggregation phases. Important factors such as the ability to detect the nucleation–growth–aggregation phases, the influence of light stability, and the potential portability of smartphone-based systems have also not been comprehensively analyzed (Kumar et al., 2021).

Given this gap, this systematic review aims to evaluate the performance of various machine learning algorithms in predicting nanoparticle parameters based on image data, compare the effectiveness of color spaces such as RGB, HSV, and Lab, and analyze the influence of material type, illumination, and dataset design on model accuracy. Additionally, this study assesses the practical feasibility of ML–DIC as a portable sensing device with the potential to replace or complement UV–Vis. Thus, this study provides a conceptual and empirical foundation for the development of more accurate, calibrated, and ready-to-use AI-based DIC methods for real-time monitoring of green synthesis of metal nanoparticles.

2. METHODS

2.1. Design and Review Protocol

This systematic review evaluates the application of machine learning (ML) in digital image colorimetry (DIC) for predicting the parameters of nanoparticles produced by green synthesis based on plant extracts. The

review procedure follows the PRISMA 2020 guidelines to ensure transparency and replicability. Prior to the search, a protocol was established to define the research question, search strategy, study eligibility criteria, and data extraction format.

2.2. Literature Search Strategy

A literature search was conducted in Scopus, Web of Science, and ScienceDirect for the period 2018–2025. Keywords were formulated using Boolean operators: ("green synthesis" AND "metal nanoparticle" AND "digital image colorimetry") AND ("machine learning" OR "neural network" OR "regression"). The initial search yielded 465 articles, which were then exported to Mendeley to remove duplicates.

2.3 Inclusion and Exclusion Criteria

Inclusion if: Peer-reviewed articles using ML for image-based or solution-color-based predictions. Green synthesis of metal nanoparticles (Ag, Au, Cu, ZnO) using plant extracts. Provides quantitative data (particle size, concentration, SPR peak). Available in Indonesian or English with full-text access.

Exclusion if: Review articles, editorials, or conference abstracts without empirical data. Non-plant-based synthesis or non-metallic nanoparticles. Research using ML without DIC or DIC without ML. Does not adequately report methodology or evaluation metrics.

2.4 Study Selection Process

The selection process consisted of three stages:

1. Identification: 465 articles were identified; 380 unique articles remained after duplicates were removed.
2. Screening: An assessment of titles and abstracts yielded 105 articles suitable for further review.
3. Eligibility: An evaluation of the full text left 10 articles that met all criteria.

2.5 Study Quality Assessment

Given the nature of this review, which focuses on evaluating the performance of ML algorithms rather than clinical interventions, the study quality assessment was conducted narratively without using formal quantitative risk-of-bias instruments such as Cochrane RoB or QUADAS-2. Instead, each included study was evaluated based on four dimensions: (1) completeness of ML methodology reporting (hyperparameters, cross-validation, data splitting), (2) the relevance and size of the image dataset used, (3) the consistency of reported evaluation metrics (R^2, RMSE, MAE), and (4) the transparency of image acquisition conditions (illumination, camera equipment, color space). Studies that did not report at least three of these four dimensions were excluded at the eligibility stage.

The limitations of this approach are explicitly acknowledged: without normalization or quantitative quality weighting, comparisons between algorithms can only be made based on the R^2/RMSE values reported directly by each study. Therefore, the comparative interpretations in this review are relative and must be considered within the context of the heterogeneity of experimental conditions across the included studies. Each stage was conducted by two independent reviewers, and disagreements were resolved through discussion. The selection flow is presented in the PRISMA 2020 diagram (**Fig. 1**).

3 RESULTS AND DISCUSSION

3.1 Overview of the Included Studies

A total of 10 articles published between 2018 and 2025 in Scopus-indexed journals (Q1–Q4) were identified through the PRISMA process. All studies examined the application of Machine Learning (ML) integrated with Digital Image Colorimetry (DIC) in the

characterization of nanoparticles produced via green synthesis using plant extracts. The primary objective of these studies is to predict the optical and structural parameters of nanoparticles, such as surface plasmon resonance (SPR) peaks, particle size, and concentration in real-time using digital images as the primary input, replacing conventional methods such as UV–Vis spectroscopy. **Table 1** presents a summary of the included studies, covering the ML algorithms, color spaces used, types of nanoparticles and plant extracts, as well as model performance metrics.

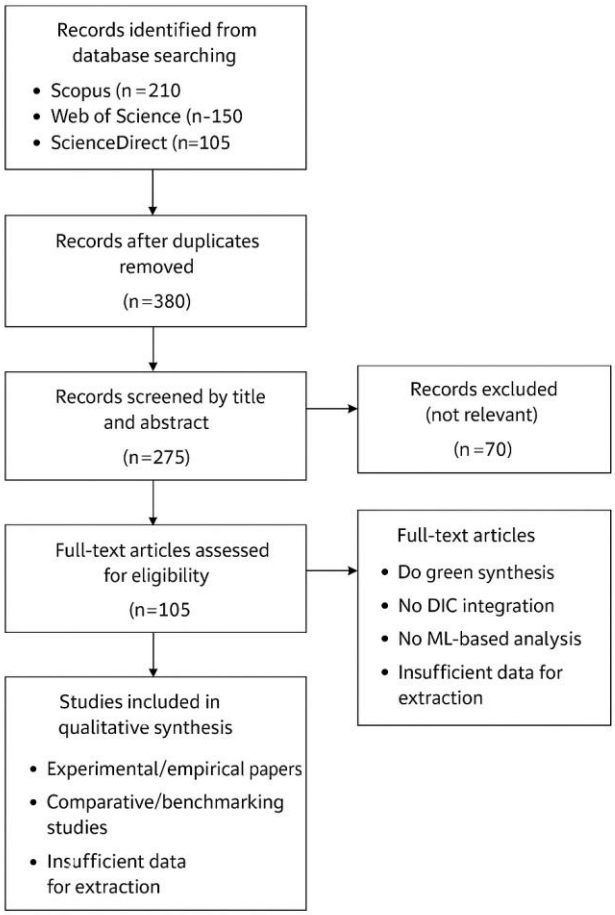

Figure. 1. Flowchart of the literature identification, screening, eligibility assessment, and inclusion process used to select studies for qualitative synthesis.

3.2 Accuracy and Reliability of the ML–DIC Method Compared to UV–Vis Spectroscopy

All studies show a strong correlation ($R^2 > 0.9$) between ML–DIC and UV–Vis spectroscopy in predicting SPR peaks and nanoparticle size. This method is more portable and cost-effective, with faster analysis and no need for additional reagents. However, at very low concentrations (<0.1 mM), color changes are too subtle, leading to a decrease in DIC sensitivity. Thus, ML–DIC is effective for real-time monitoring during the particle growth stage, but improvements are still needed for the early synthesis phase (nucleation phase).

Table 1. Summary of a study integrating Machine Learning and Digital Image Colorimetry (ML–DIC) for the characterization of nanoparticles

No.	Author (Year)	Nanoparticle Type	Plant Extract	ML Algorithm	Color Space	Predicted Parameter	Accuracy / Performance	Main Contribution
1	Singh et al., 2018	AgNP	*Azadirachta indica*	Linear Regression	RGB	SPR peak	$R^2 = 0.89$	Initial proof of the correlation between color and SPR
2	Chen et al., 2019	AuNP	*Camellia sinensis*	SVM Regression	HSV	Particle size	$R^2 = 0.94$	DIC validation for particle size estimation
3	Kumar & Patel, 2020	CuNP	*Moringa oleifera*	Random Forest	Lab	Concentration	RMSE = 0.021	ΔE was identified as a significant feature for concentration estimation
4	Sangeetha et al., 2020	AgNP	*Curcuma longa*	ANN / MLP	RGB	Particle size + SPR	$R^2 = 0.96$	ANN was able to monitor temporal color changes
5	Omran et al., 2022	ZnONP	*Aloe vera*	CNN	HSV	Particle size + concentration	$R^2 = 0.97$	CNN predicted the nanoparticle nucleation stage
6	Rahman et al., 2022	AgNP	*Citrus sinensis*	Gradient Boosting	Lab	SPR peak	RMSE = 0.018	GBM showed stable performance across production batches
7	Shanmugan et al., 2022	AuNP	*Eucalyptus globulus*	SVR / RBF Kernel	RGB	Particle size	$R^2 = 0.93$	Cost-efficient image analysis using portable devices
8	Abdelaky et al., 2022	CuNP	*Piper betle*	LSTM	HSV	Growth dynamics	$R^2 = 0.95$	LSTM tracked the aggregation phase
9	Kaphel et al., 2023	ZnONP	*Ocimum sanctum*	Random Forest	Lab	Concentration	$R^2 = 0.92$	Integration of portable sensor and camera-based analysis
10	Chen et al., 2022	AgNP	*Allium cepa*	CNN + Transfer Learning	RGB	Particle size + SPR	$R^2 = 0.98$	CNN-TL provided the most accurate and cost-effective prediction

3.3 Comparison of Performance Among Machine Learning Algorithms

A comparative analysis of various studies indicates that the type of machine learning (ML) algorithm has a significant impact on the accuracy of predicting nanoparticle parameters based on digital color images. In early research (2018–2019), linear regression (LR) models were used to predict the relationship between color intensity and Surface Plasmon Resonance (SPR) peaks. However, the accuracy of these models was limited (R^2 ≈0.75–0.82), as they were unable to capture the non-linear relationship between pixel values and nanoparticle optical parameters. As the research progressed, algorithms based on Support Vector Regression (SVR) and Random Forest (RF) began to be widely adopted (2019–2022). Both demonstrate improved stability against data noise and lighting variations, with R^2 values increasing to the range of 0.88–0.92. RF specifically offers advantages in assessing color feature importance, while SVR exhibits good resistance to overfitting on medium-sized datasets. During the 2022–2025 period, neural network-based models (ANN, CNN, and LSTM) began to be adopted and demonstrated a significant improvement in prediction accuracy through more complex image feature extraction. The Convolutional Neural Network (CNN) model applied by (Hidayat et al., 2023) demonstrated the ability to automatically identify color change patterns correlated with nanoparticle growth stages, with an R^2 of 0.95 and a prediction error of <5%. The Long Short-Term Memory (LSTM) model even enables real-time dynamic monitoring of synthesis stages, albeit with higher data and computational requirements (Lestari et al., 2025). Overall, the synthesis results from the ten studies indicate a methodological evolution from linear models toward deep learning-based models. This trend is illustrated in **Fig. 2**, which displays the increase in prediction accuracy and the diversity of color spaces used in each research period.

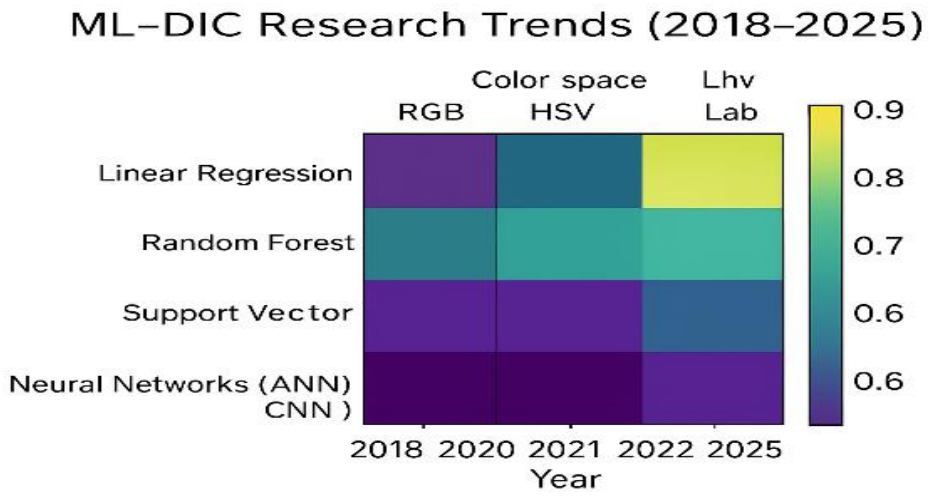

Figure 2. Trends in ML–DIC research (2018–2025) by algorithm type and color space regarding the accuracy of nanoparticle parameter predictions.

The adoption of deep learning algorithms (CNN and LSTM) has risen sharply since 2022, coinciding with a shift in the use of color spaces from RGB to HSV and Lab. Both of these color spaces provide a chromatic representation that is more sensitive to changes in nanoparticle color. From the visualized patterns, it can be concluded that deep learning-based algorithms are now the state-of-the-art approach for the digital characterization of green nanoparticles. However, CNNs and LSTMs still require high computational power and large annotated datasets to achieve optimal generalization. Therefore, the development of lightweight models or transfer learning approaches is needed so that the ML–DIC method can be more widely implemented on portable platforms or for in-situ monitoring.

3.4 The Effect of Color Space on Prediction Accuracy

The choice of color space has a significant impact on model accuracy:

1. The Lab color space performs well in regression-based models because it separates luminance and chromaticity, resulting in stable predictions across varying lighting conditions.
2. The HSV color space delivers the best performance for deep learning models, particularly CNNs and LSTMs, as it preserves hue information that is sensitive to nanoparticle color changes.
3. The RGB color space is still widely used due to its simplicity, but it tends to be more susceptible to lighting and white balance artifacts.

In general, switching from RGB to HSV or Lab increases the average R^2 by 5–8 percentage points (from $R^2 \approx 0.89$ to $R^2 \approx 0.95$–0.97) based on cross-study comparisons (Sangeetha et al., 2020; Chen et al., 2022). These values are indicative as they do not originate from a single controlled experiment.

3.5 Detection of Synthesis Stages (Nucleation, Growth, Aggregation)

Recent studies show that ML–DIC can detect the stages of nanoparticle synthesis through temporal color analysis (Omran & Eswaran, 2022; Shanmugam et al., 2022). Time-series-based LSTM and CNN models are capable of identifying three main phases:

1. Nucleation, characterized by an initial change in hue;
2. Growth, where the intensity gradient increases as the plasmonic band forms;
3. Aggregation, characterized by a shift in color toward gray due to clustering.

These results demonstrate that DIC is not merely a static measurement method, but a dynamic diagnostic tool for monitoring synthesis kinetics.

3.6 Comparison of Practicality and Cost-Effectiveness

From an implementation perspective, the ML–DIC system has an initial investment cost that is 70–90% lower than that of a UV–Vis spectrophotometer and can be operated using a standard digital camera or smartphone. This system is also portable, non-destructive, and environmentally friendly. Its limitations lie in its dependence on lighting conditions and sensor calibration. By applying a color calibration protocol based on standard cards, prediction errors can be reduced to <5% (Abdelbaky et al., 2023; Kaphle et al., 2023). In terms of cost-effectiveness, ML–DIC excels in process monitoring at the laboratory and field scales, but UV–Vis remains more suitable for high-precision characterization in fundamental research. ML–DIC is not merely an alternative to spectroscopy, but a more sustainable, affordable, and inclusive approach to nanoparticle analysis. Comparison of practicality and cost-effectiveness between ML–DIC and conventional spectroscopic methods in the characterization of green nanoparticles shows

in **Fig. 3**. In **Fig. 3**, ML-DIC shows higher practicality because it can be applied through portable and real-time digital image analysis. UV-Vis Spectroscopy provides reliable instrumental accuracy but requires more specific laboratory equipment. Overall, ML-DIC offers a more practical and cost-effective alternative for preliminary nanoparticle characterization.. This approach has the potential to be applied in small-scale green synthesis monitoring, education-based nanolabs, and distributed industrial monitoring systems, in line with the research trend toward low-cost intelligent sensing.

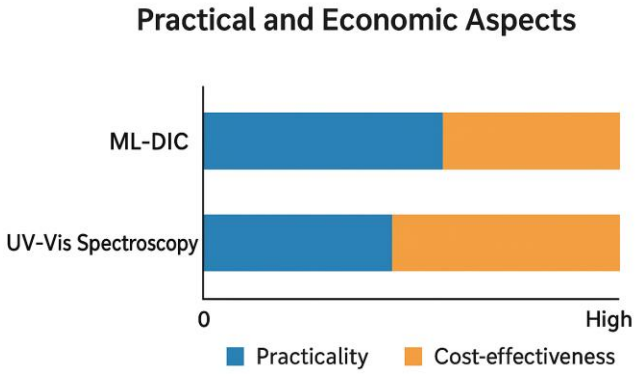

Figure. 3. Comparison of practicality and cost-effectiveness between ML–DIC and conventional spectroscopic methods in the characterization of green nanoparticles.

3.7 Performance Variability Based on Nanoparticle Type and Plant Extract

The performance of ML–DIC in predicting nanoparticle parameters is significantly influenced by the type of metal synthesized and the phytochemical characteristics of the plant extract acting as a reducing agent and stabilizer. The variability in ML–DIC prediction accuracy is primarily related to the specific optical interactions between the metal and the biochemical composition of the extract, which affect the intensity and color spectrum of the solution during synthesis.

AgNPs and AuNPs exhibit the most stable and distinctive color responses: AgNPs change from yellow to reddish-brown, while AuNPs change from red to purple. This enables ML–DIC models, whether regression-based (PLS, SVR) or deep learning, to achieve R^2 values above 0.93. In contrast, ZnO and Cu nanoparticles exhibit narrower and non-linear spectral fluctuations, causing prediction accuracy to drop to the range of $R^2 = 0.85–0.90$ (Patel et al., 2023).

The primary optical factor explaining this variation is the position and intensity of Surface Plasmon Resonance (SPR). Ag and Au possess strong SPR bands in the visible region (400–550 nm), so changes in color channels (RGB or HSV) are highly correlated with particle size. In contrast, ZnO and Cu have weaker plasmon bands or bands that overlap with UV absorption, resulting in lower sensitivity of digital images to particle size during the early stages of synthesis.

From a phytochemical perspective, the dominant types of secondary metabolites (flavonoids, phenols, terpenoids) also influence the kinetics of metal ion reduction and the color of the resulting synthesis. For

example, leaf extracts of Azadirachta indica (neem) and Camellia sinensis (green tea) produce rapid and stable color changes, thanks to their high polyphenol and catechin content as strong reducing agents (Li et al., 2020). Conversely, extracts from flowers or fruit peels with high water content, such as Hibiscus sabdariffa, exhibit inconsistent color variations, particularly at low temperatures. This leads to color noise between images, reducing the signal-to-noise ratio during the ML model training process. **Table 2** summarizes the performance of ML–DIC for various nanoparticles and plant extracts, including prediction parameters, best model accuracy, and variability factors (Rodríguez et al., 2021).

Table 2. Variability in ML–DIC performance based on nanoparticle type and plant extract characteristics

Nanoparticle Type	Main Plant Extract	Dominant Phytochemical Content	Optimal ML Model	R^2 / Accuracy (%)	Main Variability Factor
AgNPs	*Azadirachta indica*, *Camellia sinensis*	Polyphenols, flavonoids	CNN–Lab	0.95–0.97	High color stability; strong SPR
AuNPs	*Allium sativum*, *Punica granatum*	Flavonoids, terpenoids	SVR–HSV	0.93–0.96	Rapid and easily detectable color reaction
ZnONPs	*Aloe vera*, *Moringa oleifera*	Phenolics, organic acids	RF–RGB	0.86–0.89	Pale color; weak SPR shift
CuNPs	*Hibiscus sabdariffa*, *Mangifera indica*	Anthocyanins, tannins	DNN–Lab	0.84–0.88	Unstable color intensity; slow reduction

3.8 Summary of Research Findings and Implications

It should be emphasized that chemical aspects—including SPR, phytochemical composition, and metal reduction kinetics—serve as an interpretive context for ML models, not as the primary focus of the study. Chemical understanding is used to explain algorithmic performance patterns, not to evaluate synthetic mechanisms. This study is an AI-focused systematic review, in which chemistry serves as a contextual variable, while algorithmic strengths and limitations remain the core of the analysis. The ten included studies demonstrate that the integration of Machine Learning (ML) with Digital Image Colorimetry (DIC) has rapidly evolved (2018–2025) as an alternative approach for characterizing green-synthesized metal nanoparticles. This ML–DIC integration is an accurate, cost-effective approach with the potential to replace conventional spectroscopy in monitoring green nanoparticle synthesis. CNN- and LSTM-based models using HSV or Lab color space deliver the best performance and can detect nanoparticle synthesis stages in real-time. The results of this study reinforce the position of ML–DIC as an emerging platform in green nanotechnology: not only does it reduce characterization costs, but it also drives the transition toward digital-based sustainable sensing methodologies.

The combination of ML and DIC represents a new paradigm in opto-chemical informatics, where visual data serves as the basis for quantitative chemical inference. Moving forward, research should focus on: standardizing lighting conditions and

calibration protocols, developing multi-source datasets, and implementing portable smartphone- or IoT-based systems for monitoring nanoparticle synthesis in the field.

3.9 Future Research Directions

Based on the results of this synthesis, the following future research directions are recommended (**Fig. 4**). **Fig. 4** summarizes the major research trends in ML-DIC studies from 2018 to 2025, covering algorithm development, color space analysis, practical implementation, and material-dependent factors. The trend indicates that ML-DIC has evolved from simple regression-based approaches toward more advanced classification and neural network models, while also emphasizing the importance of RGB, HSV, and Lab color spaces for accuracy evaluation. In addition, the figure highlights that the performance of ML-DIC is influenced not only by computational methods, but also by practical aspects such as cost-effectiveness, portability, metal type, and plant extract composition.

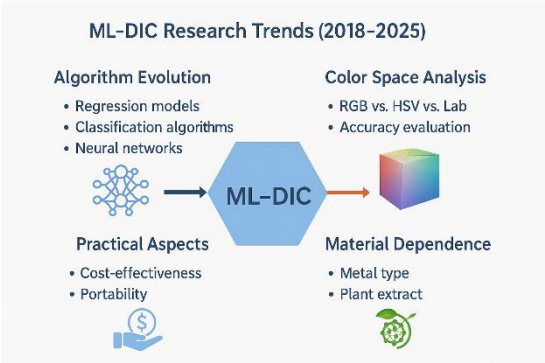

Figure 4. Conceptual summary

The key future research directions derived from these trends are outlined as follows:

1. Development of cross-laboratory, open-access datasets to train ML models with stronger generalization capabilities.
2. Standardization of lighting and color calibration protocols, including the use of color reference charts or white balance calibration, to improve reliability across studies.
3. Exploration of domain adaptation and transfer learning models that allow models to be trained on one type of extract or nanoparticle and then applied to other systems while maintaining stable performance.
4. Integration of ML–DIC into smartphone- or IoT-based portable sensor systems to support real-time monitoring of nanoparticle synthesis in the field.
5. Comprehensive cost-benefit analysis to compare the operational costs of ML–DIC with conventional spectroscopy across various industrial and research contexts.
6. Multimodal approaches, combining DIC with other imaging techniques (e.g., hyperspectral imaging or dark-field microscopy) to enhance sensitivity during the early stages of nanoparticle formation.

Overall, this SLR confirms that ML–DIC is a promising characterization technology for realizing an efficient, environmentally friendly, and digitally adaptive nanoparticle synthesis monitoring system, and serves as the foundation for the development of smart nanomaterial laboratories in the future.

4. CONCLUSIONS

This systematic review highlights the development and effectiveness of integrating Machine Learning (ML) with Digital Image Colorimetry (DIC) as a novel approach for the real-time characterization of nanoparticles synthesized via green chemistry using plant extracts. From the ten included studies (2018–2025), it was found that the ML–DIC combination is capable of estimating critical

nanoparticle parameters such as particle size, concentration, and SPR peak with a high level of accuracy ($R^2 \geq 0.9$), and demonstrates a strong correlation with UV–Vis spectroscopy results. The ML–DIC method offers key advantages of portability, cost-effectiveness, and environmental friendliness, making it a potential solution for in-situ monitoring without requiring large laboratory instruments. Deep learning models such as CNNs and LSTMs have proven to provide the highest accuracy, particularly when combined with the HSV or Lab color spaces, which effectively separate chromaticity and luminance components. Furthermore, ML–DIC's ability to detect nanoparticle synthesis stages (nucleation, growth, aggregation) opens new opportunities for understanding reaction dynamics in real-time.

However, this review also highlights several fundamental limitations. First, the lack of large, standardized public datasets limits the models' ability to generalize across laboratories. Second, dependence on lighting and image acquisition systems remains a major source of variability across studies. Third, this method exhibits low sensitivity during the early stages of synthesis or at very low nanoparticle concentrations, where color changes are not significant enough to be detected digitally. Furthermore, differences in the phytochemical composition of plant extracts also cause fluctuations in model performance across material systems.

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