

Article

AI-Enabled Compact and Efficient Dynamic Light Scattering System for Precise Microparticle Sizing

Yongxin Zhang ¹, Shijie Fu ¹, Qian Zhang ¹, Xinyi Chen ¹ , Jiyu Feng ¹, Jin Cui ^{2,*} and Bin Ai ^{1,*} 

¹ Chongqing Key Laboratory of Bio-Perception & Intelligent Information Processing, School of Microelectronics and Communication Engineering, Chongqing University, Chongqing 401331, China; 202212021019@stu.cqu.edu.cn (Y.Z.); 202412021008@stu.cqu.edu.cn (S.F.); 202212131100t@stu.cqu.edu.cn (Q.Z.); chenxy@cqu.edu.cn (X.C.); 202312131042t@stu.cqu.edu.cn (J.F.)

² United Microelectronics Center Co., Ltd., Chongqing 401332, China

* Correspondence: jin.cui@cume.cn (J.C.); binai@cqu.edu.cn (B.A.)

Abstract: A cost-effective and efficient AI-DLS framework integrating dynamic light scattering (DLS) with artificial intelligence (AI) enables precise microparticle size characterization. A compact DLS system was developed using a helium–neon laser, high-frequency photodetectors, and optimized optical components, achieving significant miniaturization—4.5% volume, 16.7% weight, and 25% cost of conventional systems. Advanced signal processing, such as Kalman filtering, improved data quality, while deep learning models (deep neural network (DNN), one-dimensional convolutional neural network (1D-CNN), and 2D-CNN with Gramian angular field transformations) enhanced prediction accuracy. The 2D-CNN model achieved exceptional results, with a mean absolute error of 10 nm and 99% accuracy. The AI-DLS system matched the stability and accuracy of traditional instruments, reducing test time by 80%. This scalable, low-cost solution overcomes traditional DLS limitations, offering broad accessibility for scientific and industrial microparticle characterization.

Keywords: dynamic light scattering; particle size measurement; convolutional neural networks; gram angle field



Academic Editor: Maria Antonietta Ferrara

Received: 23 December 2024

Revised: 7 February 2025

Accepted: 10 February 2025

Published: 12 February 2025

Citation: Zhang, Y.; Fu, S.; Zhang, Q.; Chen, X.; Feng, J.; Cui, J.; Ai, B. AI-Enabled Compact and Efficient Dynamic Light Scattering System for Precise Microparticle Sizing. *Appl. Sci.* **2025**, *15*, 1900. <https://doi.org/10.3390/app15041900>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Microparticles have become a cornerstone of modern nanotechnology, enabling revolutionary applications in fields such as biomedicine, energy storage, catalysis, and advanced materials [1]. Their unique physical and chemical properties are highly dependent on size, making accurate microparticle size characterization essential for both fundamental research and industrial applications [2]. A variety of microparticle characterization techniques are available, including transmission electron microscopy (TEM) [3], scanning electron microscopy (SEM) [4], atomic force microscopy (AFM) [5], and dynamic light scattering (DLS) [6]; however, these methods often face significant limitations. TEM and SEM provide high-resolution imaging and detailed morphological information but are time-consuming, require extensive sample preparation, and depend on costly, highly specialized equipment [7]. AFM, while capable of delivering precise three-dimensional surface profiles, suffers from low throughput and operational complexity, making it impractical for routine or large-scale measurements [8]. These limitations underscore the trade-offs between accuracy, cost, and accessibility in existing microparticle characterization methods.

Among the various methods available, DLS has gained significant attention due to its non-invasive nature, ease of use, and ability to rapidly measure microparticle size distributions in colloidal suspensions [9]. By analyzing the intensity fluctuations of scattered

light caused by Brownian motion [10], DLS provides a reliable estimate of particle size, particularly for monodisperse and polydisperse suspension systems [11,12]. Its ability to handle samples in their native liquid environment further enhances its utility in microparticle research [13]. Huang et al. investigated the effect of directional movement on DLS, demonstrating that the inclusion of the scattering wave vector variation due to particle directional motion significantly affects the intensity autocorrelation function (ACF) and improves the accuracy of particle size determination, especially in flowing dispersions [14]. Sdobnov et al. reviewed recent advancements in DLS imaging techniques for blood flow, highlighting their applications in brain vasculature assessment, skin perfusion monitoring, and non-invasive blood microcirculation characterization [15]. Kanter et al. introduced a novel probe head design that enables in-line monitoring of particle sizes in stirred colloidal suspensions using DLS, thus facilitating real-time process control [10]. Chicea et al. introduced an alternative method for processing DLS time series using spectral entropy and Artificial Neural Networks to predict particle size [9]. Jia et al. reviewed the application of DLS as a powerful tool for in situ microparticle sizing, focusing on metal oxide microparticles and discussing its measuring principle, instrument design, and applications [12]. The application of artificial intelligence for particle size prediction in DLS systems, particularly for handling signals heavily affected by noise, remains an area that has yet to be fully explored.

The previous studies primarily focused on the application of DLS but made minimal efforts to improve its methodology or address its inherent limitations [16]. Its reliance on the Stokes–Einstein equation to determine size necessitates the use of highly precise and sensitive instruments to reduce noise and ensure accuracy [15]. These instruments are often expensive (USD > 4000), sophisticated, and require meticulous maintenance, which can be a significant barrier to adoption for many laboratories and industries [17]. To address these challenges, there is a pressing need for novel microparticle size detection methods that combine high accuracy with affordability, ease of use, and scalability. Recent advancements in artificial intelligence (AI) have demonstrated immense potential in diverse scientific domains, including imaging, data analysis, and pattern recognition [18–20]. By leveraging AI, it is possible to automate and enhance the accuracy of microparticle characterization while reducing costs and operational complexity [21–23]. However, the integration of AI into microparticle size detection remains underexplored, leaving a critical gap in the development of innovative, accessible solutions.

Here, we present AI-DLS, a low-cost, efficient framework combining DLS signal acquisition with AI-driven modeling for accurate and scalable microparticle size characterization. The hardware system features a compact design comprising a helium–neon laser, precise optical components, and a high-frequency data acquisition system, achieving significant reductions in size (0.08 m²), weight (5 kg), and cost (USD 1000). Signal quality was enhanced using advanced preprocessing techniques, such as Kalman filtering, to minimize noise and improve reliability. Deep learning (DL) models, including deep neural network (DNN), one-dimensional convolutional neural network (1D-CNN) [24], and 2D-CNN with Gramian angular field (GAF) transformations, were employed to analyze ACFs derived from scattered light signals. Among these, the 2D-CNN with fused GAF inputs delivered the best performance, achieving a mean absolute error (MAE) of 10 nm and an accuracy of 0.99. The AI-DLS system demonstrated comparable stability and accuracy to traditional instruments while reducing test time by 80%. This integrated hardware–AI solution addresses the limitations of conventional DLS systems, offering a cost-effective, precise, and deployable tool for microparticle size characterization across diverse research and industrial applications.

2. Materials and Methods

2.1. AI-DLS

The photoelectric detector (model: AM-C10-36) was procured from Keshengda Co., Ltd., Chengdu, China. It is composed of avalanche photodiodes and their amplification circuits, with a signal amplification factor of up to 100 times. The helium–neon laser (model: ZL-HN632.8-2Mw) was obtained from Shenzhen Zhonglai Technology Co., Ltd., Shenzhen, China. The laser has a wavelength of 632.8 nm and a power of 2 mw. The data acquisition card (model: DAQ122) was supplied by Lingzhi Electronics Co., Ltd., Tianjin, China. Its sampling frequency is 200 KHz. The custom-designed 3D mold was fabricated by Jialichuang Co., Ltd., Shenzhen, China, using 3D printing services with Imagine Black SLA photosensitive resin as the material. The remaining structural components were constructed using black opaque acrylic sheets. The quartz cell, which features a threaded interface, was purchased from Wuxi Orituo Analytical Instrument Technology Co., Ltd., Wuxi, China. It is used to hold liquid polystyrene microspheres during testing. The polystyrene microspheres used for experimental testing were sourced from TSSphere Co., Ltd., Chongqing, China.

2.2. DLS Measurements

The manufacturer of the commercial DLS instrument used for performance comparison in this study was Brookhaven Instruments, with the model number NanoBrook Omni. We diluted the microsphere solution with pure water ($18 \text{ M}\Omega \times \text{cm}$) until its mass fraction was below 0.001%, and the microsphere test liquid that can be used for DLS measurement was obtained. The liquid was introduced into a cuvette, followed by ultrasonic treatment at a frequency of 40 kHz and a power output of 100 W for 1 min. Ultrasound at room temperature for 1 min does not cause a change in liquid temperature exceeding 1 degree Celsius. Therefore, temperature changes can be ignored. This process yielded a homogeneously dispersed microsphere suspension, which is suitable for DLS analysis. SEM images were obtained for each microsphere sample to serve as a reference for comparing the particle sizes determined by DLS. Measurements were performed for 15 microsphere sizes, ranging from 0 nm (pure water as the reference) to 1500 nm in 100 nm increments. Each size was measured five times over a 10 s interval, yielding a total of 80 datasets for ACF calculation and subsequent analysis. We expanded the original set of 80 ACF datasets to 160 by introducing random perturbations, aiming to enhance both dataset diversity and robustness. Specifically, we utilized Python's random number generator (version 3.9.7) with a fixed seed to ensure reproducibility. For each original dataset, a 2% random error was applied to each value, generating a new, slightly perturbed dataset. Having 5 sets of data allowed us to conduct statistical analysis and provide deeper information on data variability, which helps neural networks learn more data features and improve network accuracy.

2.3. Feature Extraction

The collected raw signal was denoised using a Kalman filter to suppress noise and enhance signal quality. Subsequently, the autocorrelation function of the denoised signal was computed, enabling the extraction of key characteristics associated with microsphere scattering.

The basis for describing Kalman filtering is the discrete time linear dynamic system model, which consists of state equations and observation equations [25]:

$$x_k = A_k x_{k-1} + B_k \mu_{k-1} + w_{k-1}, \quad (1)$$

where $x_k \in R^n$ is the state vector at time step k , $A_k \in R^{n \times n}$ is the state transition matrix, which describes the evolution of the state from $k - 1$ to k . $B_k \in R^{n \times m}$ is the control input

matrix, and μ_{k-1} is the control vector (which can be ignored when there is no control input). $w_{k-1} \sim N(0, Q_k)$ represents process noise, assumed to follow a zero-mean Gaussian distribution with covariance Q_k .

$$Z_k = H_k x_k + V_k, \quad (2)$$

where $z_k \in R^p$ is the observation vector at time step k , $H_k \in R^{p \times n}$ is the observation matrix, which maps the state vector to the observation space. $v_{k-1} \sim N(0, R_k)$ represents observation noise, assumed to follow a zero-mean Gaussian distribution with covariance R_k .

The Kalman filter operates in two recursive steps: prediction and update. The prediction step propagates the current state estimate forward in time:

$$\hat{x}_{\bar{k}} = A_k \hat{x}_{k-1} + B_k \mu_{k-1}, \quad (3)$$

where $\hat{x}_{\bar{k}}$ is the predicted state at time k .

$$P_{\bar{k}} = A_k P_{k-1} A_k^T + Q_k, \quad (4)$$

where $P_{\bar{k}}$ is the predicted covariance matrix, representing the uncertainty in the predicted state.

The update step incorporates the observation to refine the predicted state:

$$K_k = P_{\bar{k}} H_k^T A_k^T (H_k P_{\bar{k}} H_k^T + R_k)^{-1}, \quad (5)$$

where K_k is the Kalman gain matrix, which determines the balance between the predicted state and the measurement.

$$\hat{x}_k = \hat{x}_{\bar{k}} + K_k (z_k - H_k \hat{x}_{\bar{k}}), \quad (6)$$

where $(z_k - H_k \hat{x}_{\bar{k}})$, is the innovation, representing the difference between the observed and predicted values.

$$P_k = (I - K_k H_k) P_{\bar{k}}, \quad (7)$$

where P_k is the updated covariance matrix, representing the uncertainty in the updated state.

The autocorrelation function is mathematically defined as the expectation of the product of the signal and its lagged version:

$$R_{xx}(\tau) = E[x(t) \times x(t + \tau)], \quad (8)$$

where $R_{xx}(\tau)$ is the autocorrelation function at lag τ , $E[\cdot]$ denotes the expectation operator, $x(t)$ is the signal or time series under analysis, and τ is the time lag.

The Frobenius norm is a measure often used for matrices, and it extends the concept of the Euclidean norm to matrices. It is named after the German mathematician Ferdinand Frobenius.

Calculation for a matrix:

$$\text{For a matrix } A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}, \text{ the Frobenius norm is given by}$$

$$\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2}$$

The Kalman filter, implemented through the pykalman package, was employed for signal smoothing. For the Kalman filter configuration, measurement variance was set to 1.0, and process variance to 1×10^{-5} . The filter was initialized with a mean of 0 and a covariance of 1 for the initial state, with identity matrices for both observation and transition matrices.

2.4. Algorithms

The ACF calculation was performed using the Pandas library (version 2.3.3) functions within the PyCharm Community (version 2022) software environment. The computed ACF values were normalized to their maximum and minimum, and particle size was used as the corresponding label for the ACF. The resulting dataset was then used to train the models using a 5-fold cross-validation strategy. The DNN, 1D-CNN, and 2D-CNN models were implemented and trained in the TensorFlow 2.4 framework, also within the PyCharm Community environment. For the DNN model, a batch size of 2 and 700 epochs were used; for the 1D-CNN model, a batch size of 2 and 1200 epochs were applied; and for the 2D-CNN model, a batch size of 8 and 400 epochs were employed. The MSE was selected as the loss function for all models, while the MAE was chosen as the evaluation metric to assess model performance. All processing was conducted on a desktop computer equipped with an Intel i7-13700KF CPU @ 3.4 GHz, with 64 GB RAM sourced from Intel Corporation, Santa Clara, CA, USA, and an NVIDIA GeForce RTX 4080 GPU sourced from NVIDIA Corporation, Santa Clara, CA, USA.

Our dataset exclusively comprises integer-sized microspheres (100–1500 nm) due to their ease of acquisition and testing convenience. All data in this dataset are thus integers. In machine learning, the test set and the training set are two non-overlapping subsets derived from the same whole, so the results on the test set can be considered as a reflection of its actual performance. While our dataset is relatively small compared to large-scale ones, its effectiveness lies in its quality and representativeness. Our study prioritizes striking a balance between dataset size and achieving accurate results.

2.5. Characterization

The diluted microsphere solution was dropped onto the surface of a silicon wafer for SEM measurement. SEM characterization was performed on an Auriga-39-60 (Zeiss Auriga, Oberkochen, Germany) focused ion beam scanning electron microscope (FIB-SEM). The SEM image was taken with an EHT of 5 KV, a diaphragm of 30 mm and a WD of 5 mm.

3. Results and Discussion

Our work addresses several traditional limitations of DLS technology through the introduction of key innovations. First, we significantly reduce the cost associated with conventional DLS hardware by utilizing low-cost equipment, providing a cost-effective solution for microparticle size characterization. Second, to address the challenge of noise interference in machine learning applications, we applied PCA to high-noise ACF signals and developed a novel approach that integrates GADE, GASF, and CNN. This method demonstrates robust performance in accurately predicting particle sizes, even under noisy conditions. Third, we mitigate the time-intensive nature of traditional DLS measurements by incorporating a pre-trained model, allowing for rapid measurements within just 13 s, which marks a significant advancement in efficiency. Furthermore, our device is designed with enhanced portability and space efficiency, weighing only 5 kg with a compact volume of 0.08 m^3 , in stark contrast to commercial DLS systems that typically weigh 30 kg and occupy a volume of 0.18 m^3 .

Figure 1a illustrates the conceptual design of the AI-DLS system, which consists of a helium–neon laser (632.8 nm, 2 mW), two apertures, a focusing lens, a silicon photodiode detector, a quartz cuvette, and a data acquisition card (DAQ). Figure 1b presents the corresponding 3D model, designed with a 90° scattering measurement angle and fabricated using acrylic sheets and 3D-printed molds. The system components, including the laser, lens, and cuvette, were meticulously assembled to create the physical prototype shown in Figure 1c. The prototype features a compact footprint of 0.05 m², a height of 0.16 m, and weighs 5 kg. This represents only 4.5% of the volume (0.18 m³) and 16.7% of the weight (30 kg) of conventional DLS instruments [26]. Additionally, the AI-DLS system costs USD ~1000, just 6.3% cost of traditional models (USD 16,000) [26]. This substantial reduction in size, weight, and cost highlights the significant advancements achieved with the AI-DLS system.

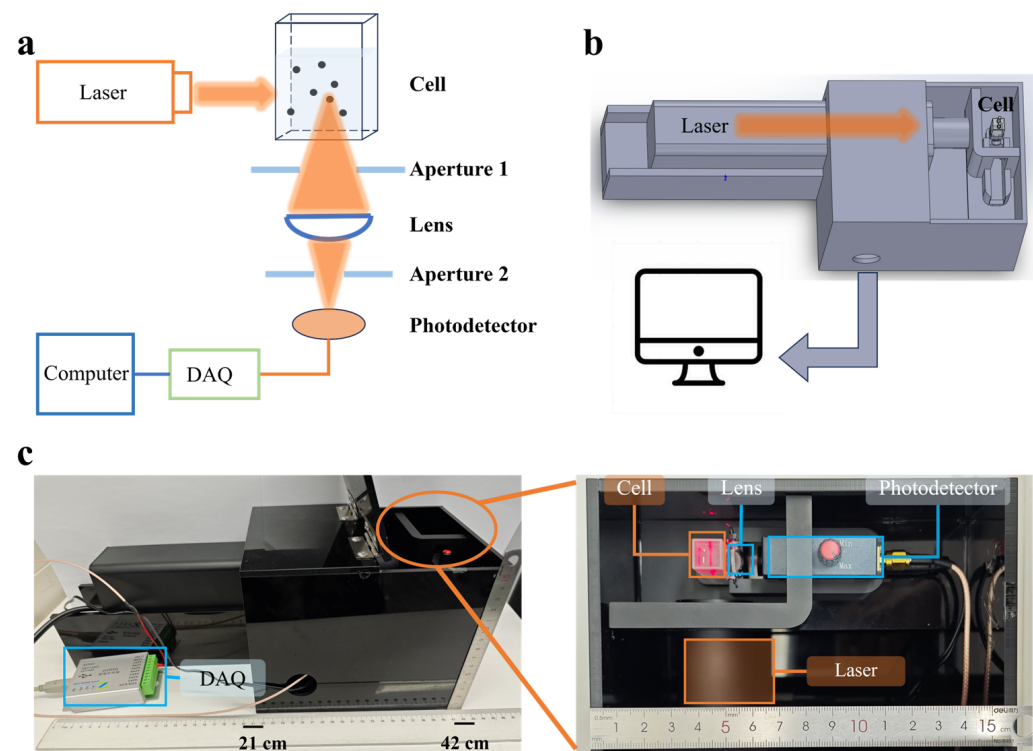


Figure 1. (a) The configuration, (b) 3D model, and (c) photos of the AI-DLS.

The laser beam is directed through a sample comprising particles suspended in a liquid medium. As the particles undergo thermal motion, they diffuse and scatter light in all directions [6]. The temporal fluctuations in the scattered light intensity are captured by a photodetector [14]. These fluctuations are intrinsically linked to the particles' diffusion coefficients, which are inversely proportional to their sizes [1,16]. The ACF, mathematically denoted as $g(\tau)$, is derived from the time series data of scattered light intensity. Here, τ signifies the lag time between successive intensity measurements [27]. The ACF quantifies the correlation between scattered light intensities at different time points separated by τ . For a monodisperse sample, the ACF exhibits an exponential decay with increasing τ , with the decay rate directly correlating to the particles' diffusion coefficient. By fitting the experimental ACF to a theoretical model, the diffusion coefficient can be extracted, and subsequently, the particle size can be determined using the Stokes–Einstein equation [28] for traditional DLS.

Monodisperse polystyrene (PS) spheres with diameters of 100–1500 nm were employed as test particles to assess the accuracy of the AI-DLS system. The diameters were confirmed via SEM. Measurements were conducted for 15 microsphere sizes, ranging from 0 nm (pure water as the reference) to 1500 nm, in 100 nm increments. Each size was measured five times with 10 s intervals, generating 80 datasets for ACF calculation and subsequent analysis. Figure 2 presents the SEM images of PS spheres with sizes of 200 nm, 400 nm, 600 nm, 900 nm, 1100 nm, and 1400 nm, alongside their corresponding raw scattering intensity signals (blue curve), the smoothed signals after applying Kalman filtering [29] (red curve), and the ACFs of the filtered signals (green curve). Theoretically, the signal should be continuous and free of any interruptions. However, in practical applications, limitations inherent to the acquisition card can lead to step-like distortions in the signal, as shown in the figure. This is a well-recognized issue and represents one of the challenges associated with using low-cost instruments. The raw scattering intensity signals are significantly contaminated by noise due to the low-cost and simple configuration, posing a substantial challenge for subsequent signal processing. As can be seen from the figure, our ACF curve has relatively small differences and does not follow the rule that the larger the particle size, the slower the decay. It is difficult to obtain accurate particle sizes using traditional formula methods. At this point, Kalman filtering technology was used to perform denoising preprocessing on these signals. Subsequently, the ACF was computed from the denoised signals. However, even after the application of Kalman filtering, the persistence of noise was evident, resulting in ACF functions that deviated from the expected exponential decay trend, exhibiting fluctuations. These fluctuations are attributed to the cumulative effect of various instrumental noise sources, which distort the autocorrelation function to such an extent that it becomes infeasible to accurately retrieve the particle size distribution. Furthermore, Supplementary Information Figure S1 provides additional SEM images and the ACFs of processed scattering intensity signals for other sizes, all of which similarly exhibit fluctuations that prevent accurate determination of particle size distributions.

In the aforementioned scenario, where the low-cost and simple instrumentation's precision was insufficient, significant noise interference arose, making it challenging to obtain accurate particle size measurements using conventional methods based on the Stokes–Einstein equation [30]. To address this issue, the potential of AI was explored for measuring particle size amidst the substantial noise introduced by the instrument. The model structures of several explored DL models are shown in Figure 3. A DNN model was designed with an input layer [31], three hidden layers, and an output layer (Figure 3a). The input layer accepts a 1×200 input vector. The first hidden layer comprises 30,000 neurons, followed by the second hidden layer with 18,000 neurons, and the third hidden layer with 10,000 neurons. The output layer contains a single neuron, providing the regression result. Figure 3b shows a 1D-CNN model, leveraging its inherent advantages in processing time-series data [32], which accepts a 1D ACF signal of size $1 \times 20,000$ as input [33]. The model, constructed using the Keras library [34], consists of two sequential convolutional layers with 32 and 64 filters, respectively, both employing a kernel size of 3 and ReLU activation functions. Following each convolutional layer, max-pooling layers with a pool size of 2 are utilized to reduce dimensionality. Subsequently, a flattening operation transforms the pooled features into a 1D vector, which is then processed by a dense layer comprising 256 neurons with ReLU activation. The output layer consists of a single neuron with a linear activation function, specifically designed for the regression task of predicting particle size [35].

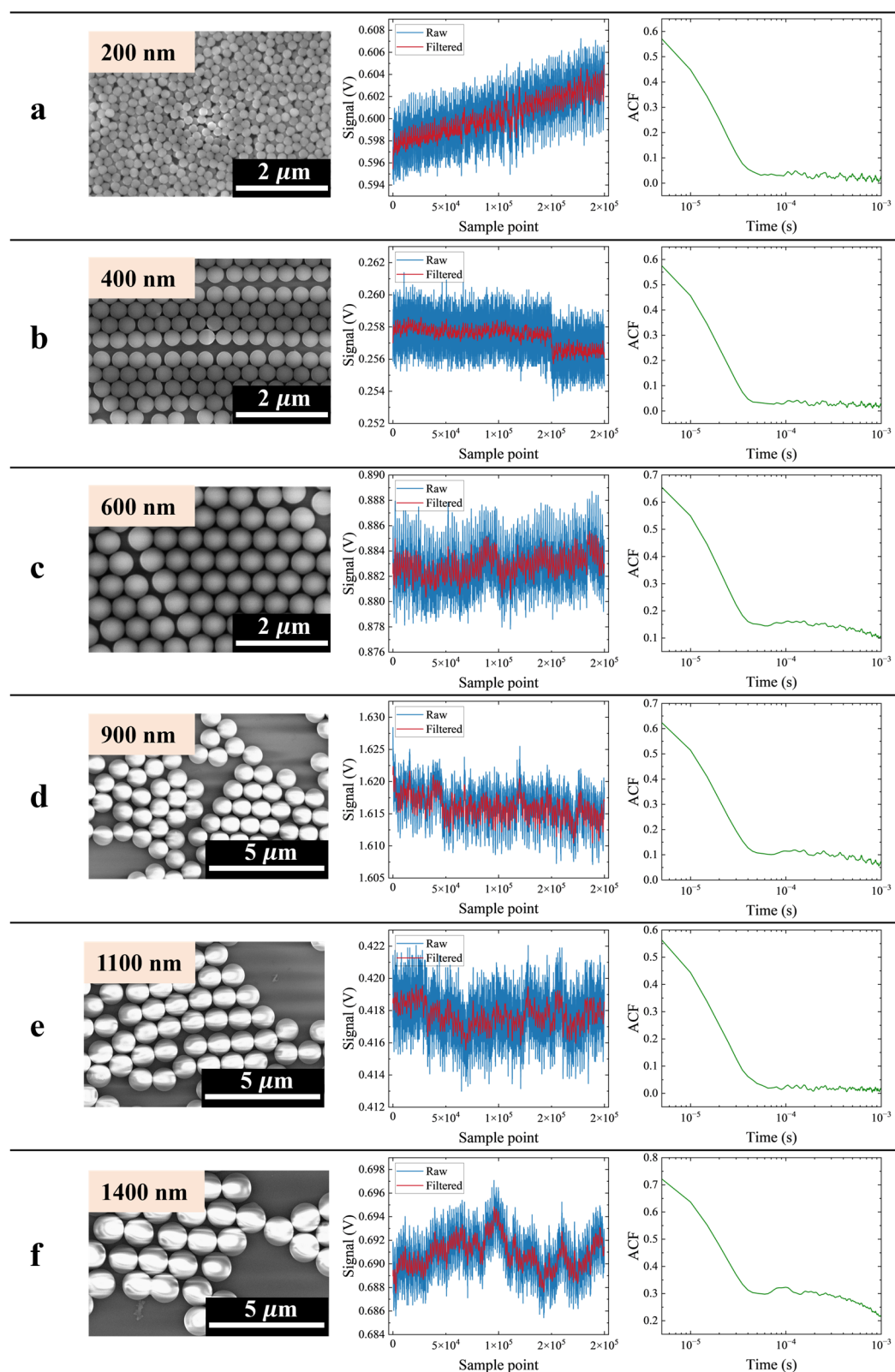


Figure 2. SEM image, raw scattering intensity signals (blue curve), the smoothed signals after applying Kalman filtering (red curve), and the ACFs (the number of lags is 1 ms) of the filtered signals (green curve) for the PS spheres with the diameters of (a) 200 nm, (b) 400 nm, (c) 600 nm, (d) 900 nm, (e) 1100 nm, and (f) 1400 nm.

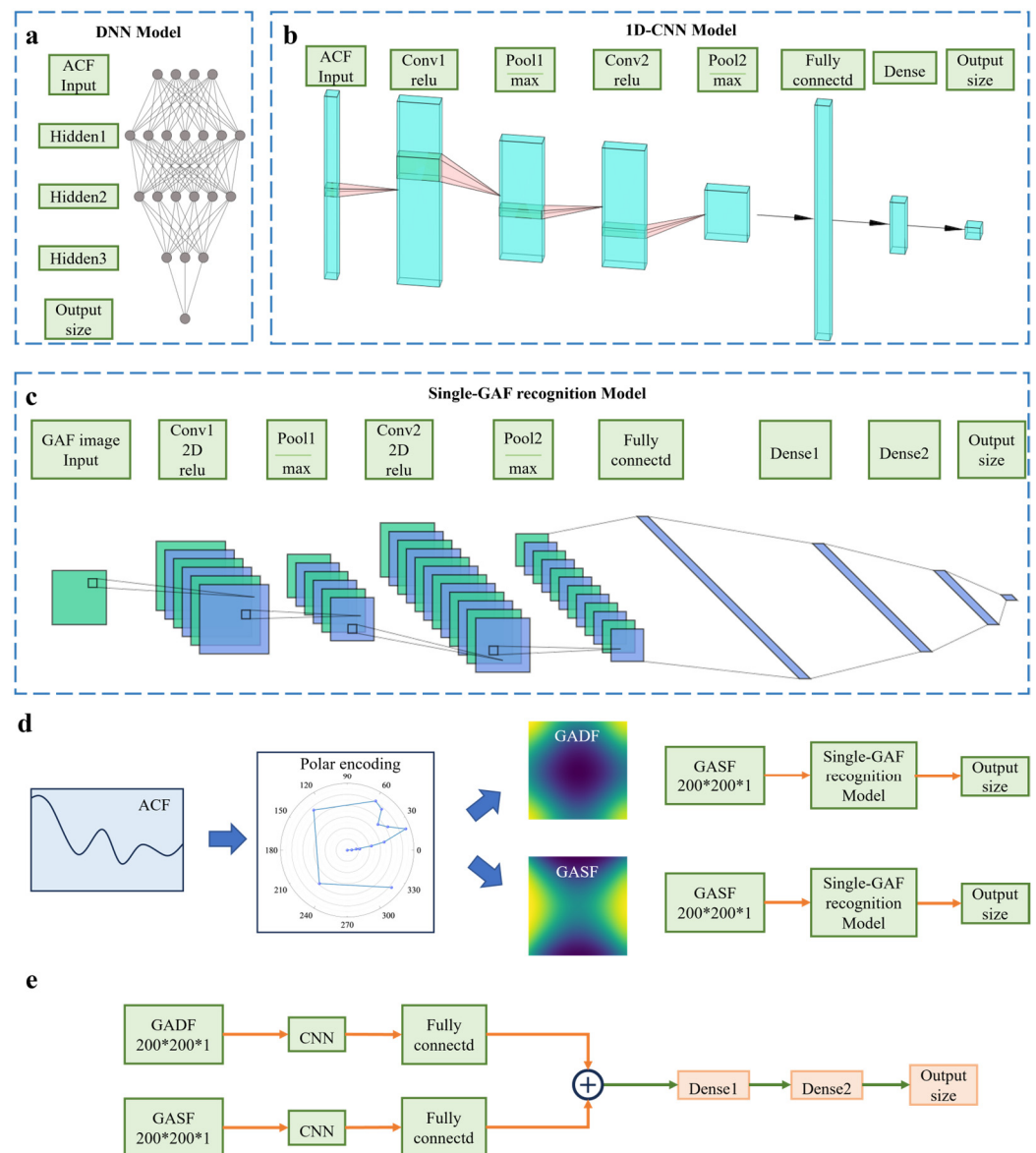


Figure 3. Structures of the (a) DNN, (b) 1D-CNN, (c) single-GAF recognition, (d) GASF, and GADF as inputs for the single-GAF recognition model, and (e) the fusion of GASF and GADF models.

The GAF is a mathematical transformation technique that converts a 1D time series or curve into a 2D representation [36], often visualized as a grayscale image or heatmap. This transformation allows the temporal patterns within the data to be preserved while enabling the use of image-based analytical methods, such as CNN, for feature extraction and analysis [37,38]. The single-GAF recognition model is defined in Figure 3c, constructed using the sequential application programming interface (API), features two convolutional layers, each equipped with eight filters of size 3×3 and ReLU activation functions, succeeded by MaxPooling layers with pool sizes of 10×10 . Following the flattening of pooled features, the model incorporates a dense layer comprising 128 neurons with ReLU activation and a dense layer comprising 64 neurons with ReLU activation. The output layer consists of a single neuron, tailored for predicting a continuous value in a regression task. As shown in Figure 3d, the process begins by normalizing the time series data to ensure that all values fall within the range of $[-1, 1]$, which is crucial for angle-based encoding. Each data point in the normalized series is then represented as an angle in polar coordinates, where the value of the data determines the angle, and the temporal sequence defines the radius. Using this polar mapping, the cosine similarity between each

pair of points in the series is computed to form a Gramian matrix. The resulting matrix encodes the temporal correlations and structural relationships within the time series, which are preserved in the two-dimensional (2D) representation. GAF is divided into Gramian angular summation field (GASF) and Gramian angular difference field (GADF), and their effects on different models also vary [39]. By transforming a one-dimensional (1D) time series into a 2D GASF/GADF, this method facilitates the application of advanced image processing techniques to time-domain data, enabling more effective feature extraction and improving model performance in tasks such as classification, regression, and clustering. Then, use the single-GAF recognition model in Figure 3c to take GADF and GASF as inputs, respectively. Figure 3e illustrates the utilization of these upscaled light intensity images for improving the single-GAF recognition model [37]. The method is to fuse GASF and GADF and input both images to the 2D-CNN network simultaneously [40]. Finally, the neurons of the two networks are connected in the fully connected layer and then passed through two layers of density to output the particle size result. Compiled with the Adam optimizer, the model employs the mean squared error (MSE) as the loss function and MAE as a supplementary metric [41]. This architectural design is optimized for capturing spatial features and delivering precise predictions.

The ACF was selected as the input to the model, as it provides a condensed yet highly informative representation of the scattering signal [9,11,12]. Directly using the raw signal as input, while feasible, would significantly increase the computational burden and prolong training time, as demonstrated in Supplementary Figure S2. Notably, the training performance of models using the raw signal was not substantially better than those employing the ACF, further validating the suitability of the ACF as the model input. To preprocess the ACF data, the initial 2000 points of each signal were extracted and compressed to 200 points by averaging every 10 consecutive values, reducing dimensionality without compromising critical features. To enhance the diversity and robustness of the dataset, the original 80 ACF datasets were further augmented to 160 by introducing random perturbations. This augmentation strategy ensured a more comprehensive dataset for model training and improved the generalization capability of the deep learning framework. The dataset of 160 samples was split into 80% training data and 20% test data for model development. During model training, the validation set consistently accounted for 10% of the data. Min-Max Normalization was applied for the dataset for rescaling feature values to a fixed range, typically [0, 1]. Each 1 s segment was transformed into a 200×200 grayscale image using the GADF and GASF techniques, resulting in a total of 640 images. These images were subsequently used for CNN-based training and analysis.

Figure 4 provides a comprehensive comparative analysis of the training dynamics and predictive performance of the DNN, 1D-CNN, and 2D-CNN models. Notably, the 2D-CNN was evaluated with three distinct input representations—GASF, GADF, and a fusion of GASF and GADF—offering a detailed assessment of their suitability for scattering signal analysis. The training and validation loss curves for all models exhibit good convergence, with no noticeable signs of significant overfitting or underfitting during training. This suggests that the models are likely well calibrated. However, to further substantiate the absence of overfitting, subsequent analysis using metrics such as MAE will be conducted to provide a more rigorous evaluation of the models' generalization performance and robustness. In terms of convergence speed, the 2D-CNN demonstrates a marked advantage, reaching convergence within 400 epochs, compared to 800 epochs for the DNN and 1200 epochs for the 1D-CNN. This efficiency highlights the capacity of the 2D-CNN to rapidly extract meaningful patterns from its two-dimensional input representations. When evaluated on the test dataset, the 2D-CNN with fused GASF and GADF input (2D-CNN (fusion)) achieves the highest accuracy, with an MAE of 10 nm. The 2D-CNN with GADF

input follows closely, achieving a 14 nm MAE, while the 1D-CNN exhibits a competitive MAE of 22 nm. The 2D-CNN with a GASF input and the DNN lags behind, with MAEs of 24 nm and significantly higher errors, respectively, reaffirming the limitations of fully connected architectures in capturing the complex dynamics of scattering signals.

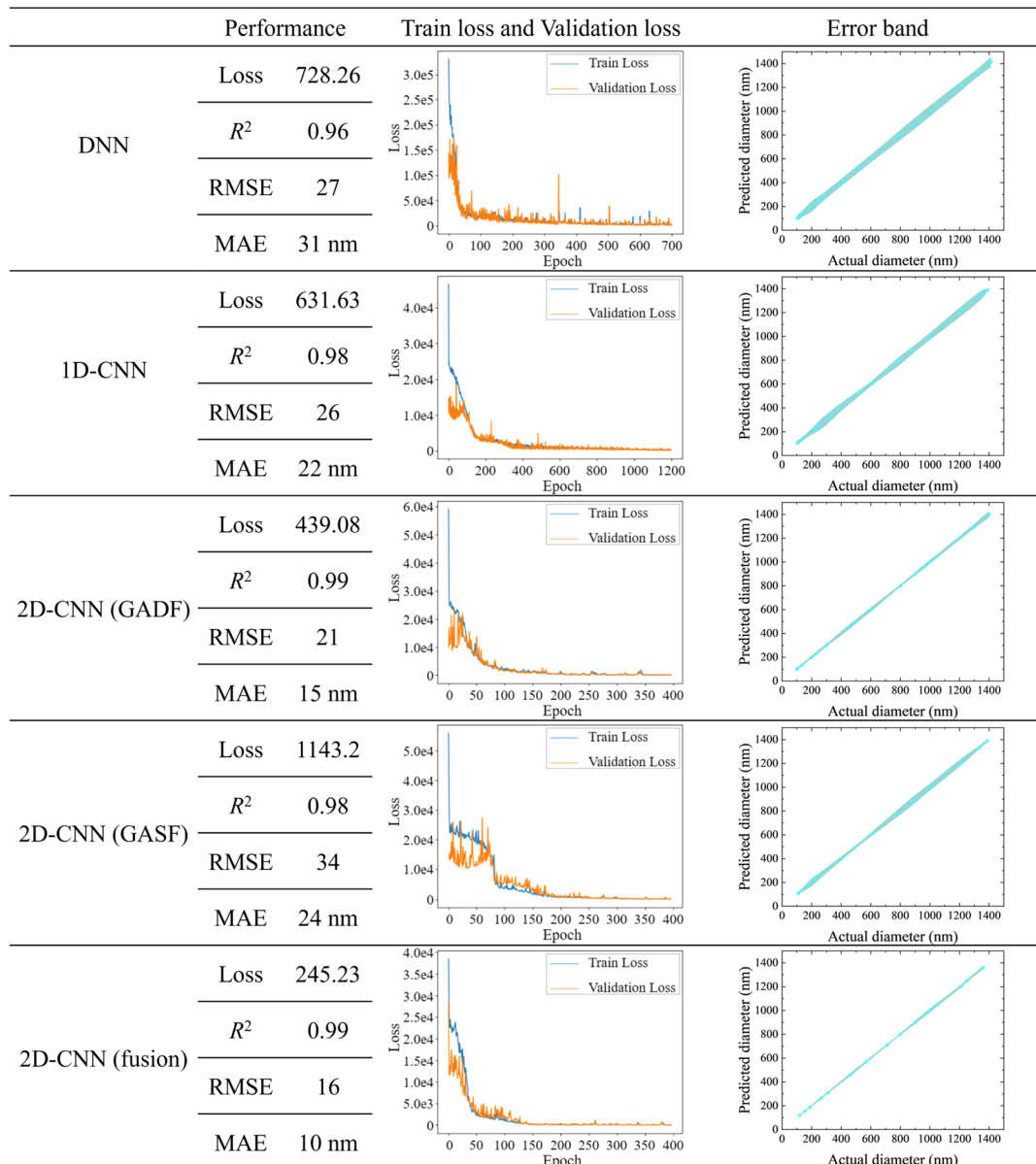


Figure 4. Loss, R^2 , RMSE and MAE of the DNN, 1D-CNN, 2D-CNN (GADF), 2D-CNN (GASF), and 2D-CNN (fusion) models.

This hierarchy of performance is further substantiated by the determination coefficients R^2 , which quantify the models' ability to explain variance in the data [40]. The 2D-CNN (fusion) and 2D-CNN (GADF) achieve near-perfect R^2 values of 0.99, underscoring their superior predictive precision. The 1D-CNN and 2D-CNN (GASF) follow with strong R^2 values of 0.98, reflecting their robust, albeit slightly less optimal, capacity for variance explanation. Conversely, the DNN trails with an R^2 of 0.96, highlighting its reduced generalization capability. These findings suggest that while both the 1D-CNN and 2D-CNN (GASF) effectively extract meaningful features, the fusion of GASF and GADF representations for the 2D-CNN facilitates a richer representation of spatial correlations, thereby driving superior performance. The error band analysis (the right column) cor-

roborates these results. The 2D-CNN (fusion) exhibits the most tightly distributed error bands along the diagonal, reflecting its exceptional consistency and accuracy. The 2D-CNN (GADF) follows closely, with slightly wider error bands, while the 1D-CNN demonstrates commendable performance, albeit with marginally larger deviations. The 2D-CNN (GASF) also performs well but exhibits slightly reduced precision. The error band provides a visual representation of the model's performance in predicting microparticle sizes. On the plot, both the horizontal and vertical axes represent particle size, and the closer a point falls to the diagonal line, the smaller the prediction error. This diagonal line represents perfect agreement between the predicted and true sizes, serving as an ideal benchmark. The width of the error band around this line indicates the magnitude of deviation or uncertainty in the model's predictions. In contrast, the DNN displays the widest error bands and the least alignment along the diagonal, emphasizing its limitations in predictive accuracy. The differences observed in model behavior and performance can be explained by the principles of DL. The 1D-CNN excels at capturing temporal dependencies and localized patterns in the 1D ACF data, offering a compelling balance between accuracy and computational efficiency. In contrast, the 2D-CNN leverages the spatial correlations embedded in the GAF representations, particularly in its fusion of GASF and GADF inputs, enabling the extraction of higher-order features that underpin its superior precision. However, this advantage comes with increased computational demands, which may constrain its utility in applications requiring rapid inference or limited resources. The DNN's relatively poor performance underscores its lack of inductive bias for handling sequential or spatial data, resulting in suboptimal feature extraction and reduced generalization.

Figure 5a–e display the ACFs for five repeated measurements of particle diameters at 100, 500, 700, 1000, and 1500 nm, respectively. The standard deviation (Std) of the five measurements for each diameter was calculated by converting the ACF curves into single values using the Frobenius norm (F) [42], with the results shown in the figures. The low variation observed is attributed to the noise from the simplified configuration and low-cost components of the AI-DLS system. PCA (Principal Component Analysis) is a statistical technique used primarily for data dimensionality reduction. It involves transforming a set of possibly correlated variables into a set of linearly uncorrelated variables, known as principal components. Despite this noise, the ACFs for different diameters remain distinct, as validated by PCA analysis, which successfully separates the ACFs for each diameter (Figure 5f). The dimensionality reduction data of PCA is used to reveal that although the ACF curve appears to have poor repeatability, there are still certain differences between data of different sizes after dimensionality reduction, thus proving that machine learning methods can separate noise from ACF signals. After inputting the ACFs into the 2D-CNN (fusion) model (Figure 5g), the predicted diameters exhibited Std/errors of 3.75 nm/0.87%, 10.17 nm/0.68%, 7.94 nm/0.24%, 15.25 nm/0.54%, and 18.29 nm/0.81% for 100, 500, 700, 1000, and 1500 nm, respectively. The errors across repeated measurements remained below 1%, meeting the stringent repeatability standards of commercial DLS instruments. The robustness of the DL model against noise and variation explains the high stability of its predictions, outperforming conventional Stokes–Einstein equation-based methods in this regard. In particular, this study underscores the limitations of traditional methodologies that rely on the Stokes–Einstein equation, which predominantly extracts particle size information through signal matching. These conventional approaches are highly susceptible to noise interference and variations in signal quality, often arising from the constraints of low-cost instrumentation, thereby resulting in pronounced fluctuations in the final outcomes. By contrast, the proposed AI-DLS model demonstrates remarkable robustness, accurately predicting particle size information even under conditions where ACF signals are significantly degraded by noise. Figure 5h compares particle size measurements across

the 100–1500 nm range between the AI-DLS system and a commercial instrument, using SEM-derived particle sizes as a reference. The results demonstrate excellent agreement between the two systems, with the AI-DLS system achieving reliability and accuracy comparable to its commercial counterpart. Notably, the AI-DLS system maintained measurement errors below 4%, averaging 1.82%, which aligns with the performance of established commercial instruments. In addition, the software interface and operational procedures of the AI-DLS are illustrated in Figure S3 in SI and detailed in Video S1, respectively, showcasing a user-friendly and streamlined workflow.

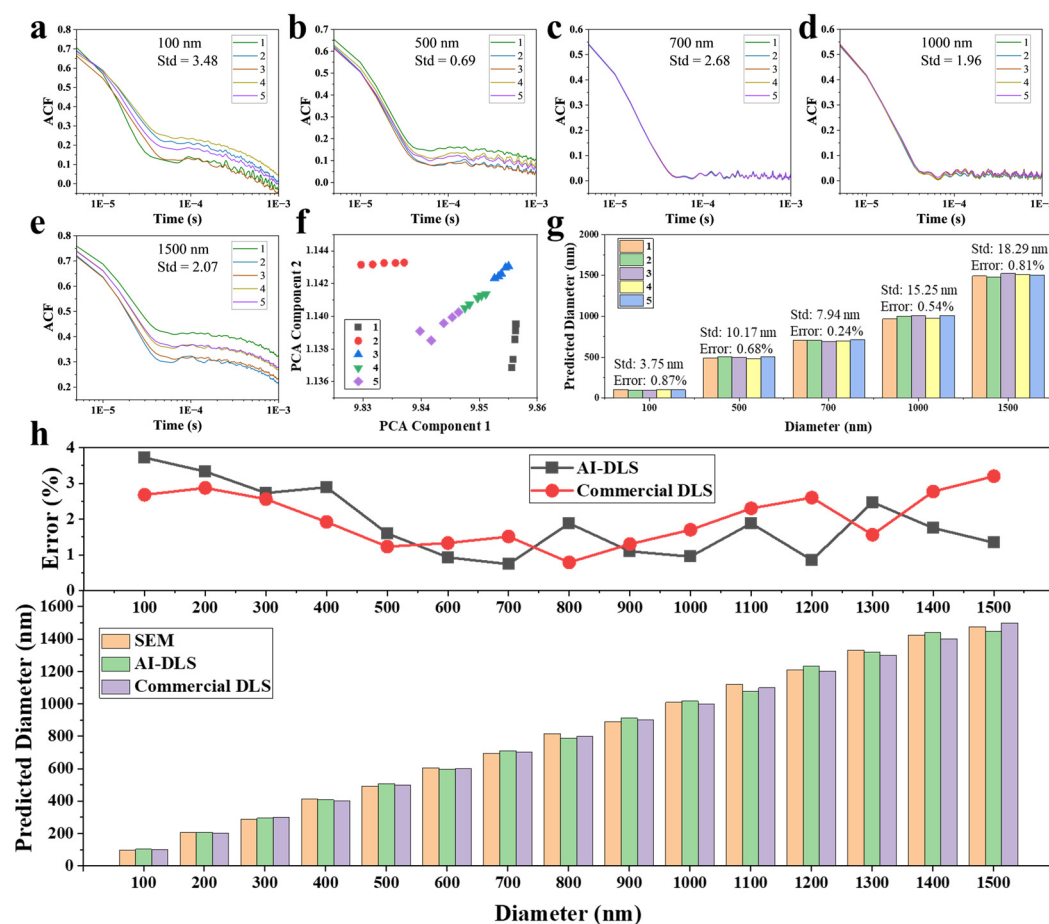


Figure 5. (a–e) ACFs for five repeated measurements at particle diameters of 100 nm, 500 nm, 700 nm, 1000 nm, and 1500 nm, respectively. (f) PCA analysis demonstrating clear separation of ACFs for the five diameters. (g) Predicted diameters with Std and error for each diameter. (h) Comparative analysis of errors and measured diameters among SEM, AI-DLS, and commercial DLS systems.

4. Conclusions

A low-cost and compact DLS system capable of overcoming the challenge of signal noise that is unmanageable by conventional methods was developed, with the detailed performance shown in Table 1. We acknowledge that directly comparing our manufacturing costs to the sales prices of commercial systems may not be entirely appropriate, as the latter includes significant markups beyond production costs. Since the exact production costs of commercial instruments are proprietary, we have assumed their manufacturing costs to be approximately one-fifth of their sales price, as suggested. Accordingly, we revised our comparison by estimating a hypothetical selling price for our device using a 5× markup on its manufacturing cost, ensuring a fairer and more accurate evaluation. The AI DLS, priced at USD 4000, is significantly more affordable than the commercial DLS (USD 16,000) while demonstrating superior accuracy (1.82% average error vs. 2.01%) and

faster testing time (<12 s vs. <60 s). Additionally, its compact size (5 kg, 0.08 m³) makes it more portable and space-efficient compared to the commercial DLS (30 kg, 0.18 m³). Both systems share similar environmental requirements (temperature: 10–30 °C, humidity: 10–80%), repeatability (<1% error), laser parameters (633–635 nm, 2 mW), and sample cell compatibility (quartz and glass). However, their software capabilities differ significantly. The AI DLS integrates advanced machine learning modes (1D-CNN, 2D-CNN), offering cutting-edge analytical capabilities, while the commercial DLS provides classic models (NNLS, CONTIN) and supports exporting raw data for further analysis. Commercial DLS can measure both monodisperse and polydisperse microspheres, while our current method is limited to monodisperse measurements. However, by expanding our dataset and leveraging AI-based approaches, size distribution prediction can also be achieved in the future. Moreover, the commercial DLS uniquely supports both 90° dynamic and backward light scattering, offering flexibility for specialized applications. The AI DLS stands out for its affordability, speed, and innovative analysis tools. Future strategies to lower system costs may include: switching to a single-channel data acquisition card, utilizing standalone avalanche photodiodes with a separate amplification circuit instead of the full component set, and optimizing 3D printing designs to make components more compact, thereby reducing material usage and simplifying assembly processes. Additionally, as part of future developments, we plan to establish a new predictive model tailored to accurately determine the particle size distribution of microspheres. This model aims to extend the system's capabilities to handle polydisperse suspensions, enabling effective prediction and analysis of more complex samples. The commercial DLS, however, remains a strong option for traditional analysis methods and advanced scattering principles.

Table 1. Performances of the AI-DLS and commercial DLS.

	AI DLS	Commercial DLS
Cost	USD 4000	USD 16,000
Average Error	1.82%	2.01%
Repeatability error	<1%	<1%
Test time	<12 s	<60 s
Weight	5 kg	30 kg
Volume	0.08 m ³	0.18 m ³
Laser parameters	633 nm; 2 mW	635 nm; 2 mW
Sample cell	Quartz cell and glass cell	Quartz cell and glass cell
Power requirements	220 V AC power	220 V AC power
Scope	Monodisperse	Monodisperse and Polydisperse
Test environment	Temperature: 10–30 °C Humidity: 10–80% relative humidity (non-condensing)	Temperature: 10–30 °C Humidity: 10–80% relative humidity (non-condensing)
Test angle	90°	Simultaneously possessing the classic 90° dynamic light scattering and backward light scattering principles

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app15041900/s1>, Figure S1: Raw signal, Kalman filtered signal, ACF curve of microspheres with diameters of 300 nm, 1200 nm and 1300 nm; Figure S2: deep learning effect of the raw signal; Figure S3: the software interface; Figure S4: The MAE versus the diameter. Figure S5: Error distribution of model prediction results (175 nm, 260 nm, 330 nm, 370 nm, 450 nm, 550 nm, 740 nm, 950 nm, 1250 nm, and 1450 nm). Video S1: operational procedures of the AI-DLS.

Author Contributions: Conceptualization, Y.Z., S.F. and B.A.; Data curation, Y.Z. and S.F.; Formal analysis, Y.Z.; Methodology, Y.Z., S.F. and J.F.; Project administration, J.C. and B.A.; Resources, Y.Z., Q.Z. and J.F.; Software, Y.Z. and X.C.; Supervision, X.C., J.C. and B.A.; Validation, Y.Z., Q.Z. and X.C.; Visualization, Y.Z., X.C. and B.A.; Writing—original draft, Y.Z., X.C. and B.A.; Writing—review and editing, B.A. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Open Project of State Key Laboratory for Supramolecular Structure and Materials (SKLSSM 202501).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data supporting the main findings of this study are available from the corresponding authors upon reasonable request.

Conflicts of Interest: Author Jin Cui was employed by the company United Microelectronics Center Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

TEM	Transmission Electron Microscopy
SEM	Scanning Electron Microscopy
AFM	Atomic Force Microscopy
DLS	Dynamic Light Scattering
ACF	Autocorrelation Function
AI	Artificial Intelligence
1D	One-dimensional
2D	Two-dimensional
DNN	Deep Neural Network
CNN	Convolutional Neural Network
GAF	Gramian Angular Field
GASF	Gramian Angular Summation Field
GADF	Gramian Angular Difference Field
MAE	Mean Absolute Error
PSPCA	PolystyrenePrincipal Components Analysis
MSE	Mean Squared Error

References

1. Liu, B.; Postnov, D.; Boas, D.A.; Cheng, X. Dynamic light scattering and laser speckle contrast imaging of the brain: Theory of the spatial and temporal statistics of speckle pattern evolution. *Biomed. Opt. Express* **2024**, *15*, 579–593. [[CrossRef](#)] [[PubMed](#)]
2. Cheishvili, K.; Kalkman, J. Scanning dynamic light scattering optical coherence tomography for measurement of high omnidirectional flow velocities. *Opt. Express* **2022**, *30*, 23382–23397. [[CrossRef](#)] [[PubMed](#)]
3. Mason, D.R.; Boleining, M.; Haley, J.; Prestat, E.; He, G.; Hofmann, F.; Dudarev, S.L. Simulated TEM imaging of a heavily irradiated metal. *Acta Mater.* **2024**, *277*, 120162. [[CrossRef](#)]
4. Cheng, M.; Lin, X.; Chen, X.; Chen, C.; Zhang, G.; Ai, B. Enhancing Plasmonic Hydrogen Sensing Through Heterogeneous Multilayer Configurations with Quantitative Mechanism Analysis. *ACS Appl. Nano Mater.* **2024**, *7*, 14203–14212. [[CrossRef](#)]
5. Heath, G.R.; Micklethwaite, E.; Storer, T.M. NanoLocz: Image Analysis Platform for AFM, High-Speed AFM, and Localization AFM. *Small Methods* **2024**, *8*, e2301766. [[CrossRef](#)]
6. Wang, M.; Shen, J.; Thomas, J.C.; Mu, T.; Liu, W.; Wang, Y.; Pan, J.; Wang, Q.; Liu, K. Particle Size Measurement Using Dynamic Light Scattering at Ultra-Low Concentration Accounting for Particle Number Fluctuations. *Materials* **2021**, *14*, 5683. [[CrossRef](#)]
7. Miyashita, S.-I.; Ogura, T.; Matsuura, S.-I.; Fukuda, E. Particle Size Measurement and Detection of Bound Proteins of Non-Porous/Mesoporous Silica Microspheres by Single-Particle Inductively Coupled Plasma Mass Spectrometry. *Molecules* **2024**, *29*, 1086. [[CrossRef](#)]

8. Zhang, J.; Ren, J.; Hu, S. AFM Imaging Defect Detection and Classification Using Deep Learning. *IEEE Access* **2024**, *12*, 132027–132037. [CrossRef]
9. Chicea, D.; Doroshkevich, A.S.; Lyubchik, A. On the Possibility of Designing an Advanced Sensor with Particle Sizing Using Dynamic Light Scattering Time Series Spectral Entropy and Artificial Neural Network. *Sensors* **2022**, *22*, 3871. [CrossRef]
10. de Kanter, M.; Meyer-Kirschner, J.; Viell, J.; Mitsos, A.; Kather, M.; Pich, A.; Janzen, C. Enabling the measurement of particle sizes in stirred colloidal suspensions by embedding dynamic light scattering into an automated probe head. *Measurement* **2016**, *80*, 92–98. [CrossRef]
11. Zhang, G.; Wang, Z.; Wang, Y.; Shen, J.; Liu, W.; Fu, X.; Li, C. Particle Size Inversion Constrained by L_∞ Norm for Dynamic Light Scattering. *Materials* **2022**, *15*, 7111. [CrossRef]
12. Jia, Z.; Li, J.; Gao, L.; Yang, D.; Kanaev, A. Dynamic Light Scattering: A Powerful Tool for In Situ Nanoparticle Sizing. *Colloids Interfaces* **2023**, *7*, 15. [CrossRef]
13. Rodriguez-Loya, J.; Lerma, M.; Gardea-Torresdey, J.L. Dynamic Light Scattering and Its Application to Control Nanoparticle Aggregation in Colloidal Systems: A Review. *Micromachines* **2023**, *15*, 24. [CrossRef] [PubMed]
14. Huang, G.; Xu, B.; Qiu, J.; Peng, L.; Luo, K.; Liu, D.; Han, P. Effect of Directional Movement on Dynamic Light Scattering. *IEEE Photonics J.* **2021**, *13*, 5000213. [CrossRef]
15. Sdobnov, A.; Piavchenko, G.; Bykov, A.; Meglinski, I. Advances in Dynamic Light Scattering Imaging of Blood Flow. *Laser Photonics Rev.* **2023**, *18*, 2300494. [CrossRef]
16. Meza-Arroyo, J.; Valdés-Hernández, J.; Domínguez-Juárez, J.L.; Quintero-Torres, R. DLS homemade setup: Reviewing first and second-order coherence and autocorrelation concepts of a light source in the context of nanoparticle sizes synthesized by PLAL. *Phys. Scr.* **2024**, *99*, 085311. [CrossRef]
17. Stock, S.; von Klitzing, R.; Rahimzadeh, A. Dynamic light scattering for particle characterization subjected to ultrasound: A study on compact particles and acousto-responsive microgels. *Sci. Rep.* **2024**, *14*, 989. [CrossRef] [PubMed]
18. Shah, A.A.; Malik, H.A.M.; Muhammad, A.; Alourani, A.; Butt, Z.A. Deep learning ensemble 2D CNN approach towards the detection of lung cancer. *Sci. Rep.* **2023**, *13*, 2987. [CrossRef]
19. Yang, Y.; Li, H.; Jones, L.; Murray, J.; Naikare, H.; Mosley, Y.Y.C.; Spikes, T.; Hülck, S.; Tripp, R.A.; Ai, B.; et al. Advancing SERS Diagnostics in COVID-19 with Rapid, Accurate, and Label-Free Viral Load Monitoring in Clinical Specimens via SFNet Enhancement. *Adv. Mater. Interfaces* **2024**, *11*, 2400013. [CrossRef]
20. Ai, Z.; Zhang, L.; Chen, Y.; Long, Y.; Li, B.; Dong, Q.; Wang, Y.; Jiang, J. On-Demand Optimization of Colorimetric Gas Sensors Using a Knowledge-Aware Algorithm-Driven Robotic Experimental Platform. *ACS Sens.* **2024**, *9*, 745–752. [CrossRef] [PubMed]
21. Diakite, A.; Jiangsheng, G.; Xiaping, F. Hyperspectral image classification using 3D 2D CNN. *IET Image Process.* **2020**, *15*, 1083–1092. [CrossRef]
22. Lee, J.; Lee, J.H.; Lee, C.; Lee, H.; Jin, M.; Kim, J.; Shin, J.C.; Lee, E.; Kim, Y.S. Machine Learning Driven Channel Thickness Optimization in Dual-Layer Oxide Thin-Film Transistors for Advanced Electrical Performance. *Adv. Sci.* **2023**, *10*, 2303589. [CrossRef]
23. Guo, Y.; Zhang, L.; Li, Z.; He, Y.; Lv, C.; Chen, Y.; Lv, H.; Du, Z. Online Detection of Dry Matter in Potatoes Based on Visible Near-Infrared Transmission Spectroscopy Combined with 1D-CNN. *Agriculture* **2024**, *14*, 787. [CrossRef]
24. Chen, H.; Liu, S.; Yang, X.; Zhang, X.; Yang, J.; Fan, S. Prediction of Sunspot Number with Hybrid Model Based on 1D-CNN, BiLSTM and Multi-Head Attention Mechanism. *Electronics* **2024**, *13*, 2804. [CrossRef]
25. Schmidt, F.; Wainwright, H.M.; Faybishenko, B.; Denham, M.; Eddy-Dilek, C. In Situ Monitoring of Groundwater Contamination Using the Kalman Filter. *Environ. Sci. Technol.* **2018**, *52*, 7418–7425. [CrossRef] [PubMed]
26. Panaco, M. Commercial DLS. 2024. Available online: <https://www.malvernpanalytical.com.cn/products/technology/light-scattering/dynamic-light-scattering> (accessed on 20 November 2024).
27. Wang, B.; Cai, T.; Cai, X.; Zhou, W.; Liu, Z. Polarized imaging dynamic light scattering for simultaneous measurement of nanoparticle size and morphology. *Particuology* **2024**, *85*, 213–223. [CrossRef]
28. Kheifets, S.; Simha, A.; Melin, K.; Li, T.; Raizen, M.G. Raizen Authors Info & Affiliations, Observation of Brownian Motion in Liquids at Short Times: Instantaneous Velocity and Memory Loss. *Science* **2014**, *343*, 1493–1496. [PubMed]
29. Van Loon, S.; Fletcher, S.J. A dynamical Gaussian, lognormal, and reverse lognormal Kalman filter. *Q. J. R. Meteorol. Soc.* **2023**, *150*, 262–274. [CrossRef]
30. Lyu, J.; Hu, T.; Liu, G.; Cao, B.; Wang, W.; Li, S. Stability evaluation of open-pit mine slope based on Bayesian optimization 1D-CNN. *Sci. Rep.* **2024**, *14*, 13995. [CrossRef]
31. Singh, S.; Bhargaw, H.N.; Jadhav, M.; John, P. A comparative analysis between deep neural network-based 1D-CNN and LSTM models to harness the self-sensing property of the shape memory alloy wire actuator for position estimation. *Smart Mater. Struct.* **2024**, *33*, 085045. [CrossRef]
32. Mou, J.; Yang, Q.; Tang, Y.; Liu, Y.; Li, J.; Yu, C. Prediction of the Remaining Useful Life of Lithium-Ion Batteries Based on the 1D CNN-BLSTM Neural Network. *Batteries* **2024**, *10*, 152. [CrossRef]

33. Wang, T.; Huang, X.; Xiao, Z.; Cai, W.; Tai, Y. EEG emotion recognition based on differential entropy feature matrix through 2D-CNN-LSTM network. *EURASIP J. Adv. Signal Process.* **2024**, 2024, 49. [\[CrossRef\]](#)
34. Yu, D.; Kong, H.; Leung, J.C.-H.; Chan, P.W.; Fong, C.; Wang, Y.; Zhang, B. A 1D Convolutional Neural Network (1D-CNN) Temporal Filter for Atmospheric Variability: Reducing the Sensitivity of Filtering Accuracy to Missing Data Points. *Appl. Sci.* **2024**, 14, 6289. [\[CrossRef\]](#)
35. Choi, Y.; Nguyen, H.-T.; Han, T.H.; Choi, Y.; Ahn, J. Sequence Deep Learning for Seismic Ground Response Modeling: 1D-CNN, LSTM, and Transformer Approach. *Appl. Sci.* **2024**, 14, 6658. [\[CrossRef\]](#)
36. Boujou, M.; Iguernaissi, R.; Nicod, L.; Merad, D.; Dubuisson, S. In-Depth Analysis of GAF-Net: Comparative Fusion Approaches in Video-Based Person Re-Identification. *Algorithms* **2024**, 17, 352. [\[CrossRef\]](#)
37. Ma, J.; Jiao, L.; Li, M. Fault Diagnosis of Planetary Gear Based on FRWT and 2D-CNN. *Math. Probl. Eng.* **2022**, 2022, 4648653. [\[CrossRef\]](#)
38. Xia, P.; He, Z.; Bai, Z.; Wang, Y.; Yu, X.; Geng, F.; Du, L.; Chen, X.; Wang, P.; Zhu, Y.; et al. A novel multi-scale 2D CNN with weighted focal loss for arrhythmias detection on varying-dimensional ECGs. *Physiol. Meas.* **2022**, 43, 104003. [\[CrossRef\]](#)
39. Wu, H.; Tang, D.; Cai, Y.; Zheng, C. Research on Early Fault Identification of Cables Based on the Fusion of MTF-GAF and Multi-Head Attention Mechanism Features. *IEEE Access* **2024**, 12, 81853–81866. [\[CrossRef\]](#)
40. Lin, X.; Cheng, M.; Chen, X.; Zhang, J.; Zhao, Y.; Ai, B. Unlocking Predictive Capability and Enhancing Sensing Performances of Plasmonic Hydrogen Sensors via Phase Space Reconstruction and Convolutional Neural Networks. *ACS Sens.* **2024**, 9, 3877–3888. [\[CrossRef\]](#)
41. Tong, J.; Li, J.; Zhang, M.; Zhang, B. Action Localization Using 2D-CNN and 3D-CNN Collaboration. *IEEE Access* **2022**, 10, 77658–77667. [\[CrossRef\]](#)
42. Böttcher, A.; Wenzel, D. The Frobenius norm and the commutator. *Linear Algebra Its Appl.* **2008**, 429, 1864–1885. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.