# Machine Learning-Based Quantitative Prediction of $Pb^{2+}$ Concentration from Silver Nanoparticle Colorimetric Images

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**ABSTRACT**
Colorimetric sensing based on silver nanoparticles (AgNP) provides a simple and low-cost method for detecting heavy metal ions through aggregation-induced color changes. However, quantitative analysis commonly requires expensive spectrophotometers, limiting field applications. This study presents a machine learning framework for predicting $Pb^{2+}$ concentration from AgNP colorimetric images using the device-independent CIELAB color space. Images were processed to extract L*, a*, and b* color features across a concentration range of 0–50 µM. A K-Nearest Neighbors (KNN) regressor, optimized with distance-based weighting and validated using 5-fold cross-validation, was employed for quantitative prediction. Model performance was evaluated using the coefficient of determination ($R^2$), mean absolute error (MAE), and root mean square error (RMSE). The optimized model achieved excellent predictive accuracy with an $R^2$ of 0.9863, MAE of 0.8073, and RMSE of 1.9797 µM. Integrated into a graphical user interface, the proposed framework demonstrates the potential of combining AgNP-based colorimetric sensing with machine learning to provide rapid, portable, and cost-effective environmental monitoring of $Pb^{2+}$ contamination.

**ABSTRAK**
Sensor kolorimetri berbasis nanopartikel perak (AgNP) merupakan metode sederhana dan berbiaya rendah untuk mendeteksi ion logam berat melalui perubahan warna akibat agregasi nanopartikel. Namun, analisis kuantitatif umumnya masih bergantung pada spektrofotometer yang mahal sehingga kurang sesuai untuk aplikasi lapangan. Penelitian ini mengusulkan kerangka kerja berbasis machine learning untuk memprediksi konsentrasi $Pb^{2+}$ dari citra kolorimetri AgNP menggunakan ruang warna CIELAB yang bersifat independen terhadap perangkat. Citra diproses untuk mengekstraksi fitur warna L*, a*, dan b* pada rentang konsentrasi 0–50 µM. Algoritma K-Nearest Neighbors (KNN) Regressor yang dioptimalkan dengan pembobotan berbasis jarak serta divalidasi menggunakan 5-fold cross-validation digunakan untuk melakukan prediksi kuantitatif. Kinerja model dievaluasi menggunakan koefisien determinasi ($R^2$), mean absolute error (MAE), dan root mean square error (RMSE). Model terbaik menunjukkan akurasi prediksi yang sangat tinggi dengan nilai $R^2$ sebesar 0,9863, MAE sebesar 0,8073 dan RMSE sebesar 1,9797 µM. Kerangka kerja yang terintegrasi dalam antarmuka pengguna grafis ini berpotensi menjadi solusi pemantauan pencemaran $Pb^{2+}$ yang cepat, portabel, dan ekonomis.

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**KEYWORDS**
Heavy metal, Machine learning, Nanoparticle

Received: 01/09/2026
Revised: 22/10/2026
Accepted: 27/10/2026
Online: 31/10/2026
Published: 31/10/2026

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10.21009/joc.13.03

## INTRODUCTION

Heavy metal contamination has emerged as one of the most pressing environmental challenges worldwide due to its persistence, bioaccumulation, and severe impacts on both ecosystems and human health. Among these contaminants, lead ($Pb^{2+}$) is regarded as one of the most toxic and widely distributed heavy metals. The World Health Organization (WHO) identifies lead as one of the ten chemicals of major public health concern, emphasizing the urgent need for effective monitoring strategies to protect vulnerable populations, including children, women of reproductive age, and occupationally exposed workers (World Health Organization, 2026). Anthropogenic activities, particularly mining, smelting, and metallurgical industries, substantially increase environmental lead emissions by releasing Pb-containing particulates into the atmosphere, which subsequently enter aquatic environments through atmospheric deposition and precipitation (Csavina et al., 2012). Unlike many organic contaminants, lead is non-biodegradable and readily accumulates throughout the food chain, posing long-term ecological risks. Even at trace concentrations, chronic exposure to $Pb^{2+}$ can induce irreversible neurological impairment, renal dysfunction, hematological abnormalities, cardiovascular disorders, and developmental toxicity, while prolonged exposure has also been associated with carcinogenic effects (World Health Organization, 2023). Consequently, the development of rapid, reliable, and accessible methods for quantitative $Pb^{2+}$ monitoring remains an important research priority.

Accurate determination of $Pb^{2+}$ concentrations has traditionally relied on laboratory-based analytical techniques, including atomic absorption spectroscopy (AAS), inductively coupled plasma mass spectrometry (ICP-MS), inductively coupled plasma optical emission spectroscopy (ICP-OES), anodic stripping voltammetry (ASV), capillary electrophoresis (CE), X-ray fluorescence spectroscopy (XRF), liquid chromatography, and UV–Vis spectroscopy (Yu et al., 2022). These methods provide excellent sensitivity and selectivity, often achieving trace- and ultra-trace-level detection. Nevertheless, their widespread implementation for routine environmental monitoring is hindered by several practical limitations, including high instrumentation costs, labor-intensive sample preparation, sophisticated laboratory infrastructure, and the requirement for trained operators. These constraints significantly restrict their applicability for rapid on-site monitoring, particularly in remote or resource-limited regions where frequent environmental surveillance is most needed.

To overcome these limitations, increasing attention has been directed toward optical sensing technologies that enable rapid and portable heavy metal detection. Among them, localized surface plasmon resonance (LSPR)-based colorimetric sensors employing silver nanoparticles (AgNP) have emerged as particularly attractive owing to their simplicity, rapid response, and high sensitivity to changes in the local dielectric environment (Roto et al., 2019; Sudarman et al., 2022). The intense LSPR absorption of AgNP produces characteristic solution colors that vary in response to nanoparticle aggregation induced by interactions with target metal ions such as $Pb^{2+}$. Consequently, $Pb^{2+}$ concentrations can be qualitatively identified through visually observable color changes and quantitatively evaluated through shifts in the optical absorption spectrum. Despite these advantages, quantitative interpretation of AgNP colorimetric responses still predominantly depends on UV–Vis spectrophotometers, whose high cost and limited portability hinder the translation of laboratory-based colorimetric assays into practical field-deployable sensing platforms.

Recent advances in computer vision and machine learning offer a promising pathway to overcome this technological barrier by replacing conventional spectroscopic measurements with intelligent image-based analysis. Instead of acquiring absorption spectra, digital images captured using widely available imaging devices, such as smartphone cameras, can encode subtle chromatic variations arising from $Pb^{2+}$-induced nanoparticle aggregation. These colorimetric responses can be transformed into quantitative numerical descriptors through color space analysis, including the perceptually uniform CIELAB color representation, thereby enabling computational extraction of features closely correlated with analyte concentration. Machine learning algorithms can subsequently establish nonlinear relationships between these image-derived features and $Pb^{2+}$ concentrations, enabling rapid quantitative prediction without the need for expensive optical instrumentation. Compared with traditional calibration approaches, machine learning offers superior capabilities for modeling complex multivariate relationships and improving prediction accuracy across varying imaging conditions.

Although several studies have explored smartphone-assisted colorimetric sensing for heavy metal detection, most investigations remain focused on qualitative classification or simple linear calibration models based on Red, Green and Blue (RGB) intensities, which are often susceptible to illumination variations and exhibit limited predictive accuracy over broad concentration ranges. Furthermore, studies employing perceptually uniform color descriptors together with supervised machine learning algorithms for quantitative $Pb^{2+}$ prediction from AgNP colorimetric images remain relatively scarce. This limitation motivates the development of a more robust image-based analytical framework capable of accurately estimating $Pb^{2+}$ concentrations directly from digital photographs.



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In this study, we propose a machine-learning-assisted colorimetric sensing framework for quantitative prediction of $Pb^{2+}$ concentration using images of AgNP. Colorimetric information extracted from the CIELAB color space was employed as input features for supervised machine learning algorithms, i.e. K-Nearest Neighbors (KNN). The predictive performances of these models were systematically evaluated and compared to identify the most accurate and reliable algorithm for $Pb^{2+}$ quantification. By integrating AgNP-based LSPR colorimetric sensing with computer vision and machine learning, this work establishes an inexpensive, portable, and intelligent alternative to conventional spectroscopic analysis, providing a practical solution for real-time environmental monitoring of lead contamination.

## METHODS

### Image Dataset Preparation

The colorimetric image dataset used in this study was derived from the published experimental results of Khan et al. (2018). The dataset represented seven $Pb^{2+}$ concentration levels (0, 1, 2.5, 5, 10, 25, and 50 μM), covering the investigated concentration range of 0–50 μM. The original study demonstrated concentration-dependent color changes in AgNP solutions resulting from interactions between $Pb^{2+}$ ions and the nanoparticle surfaces.

The original publication does not provide detailed specifications of the camera or imaging equipment, illumination conditions, camera-to-sample distance, sample positioning, background configuration, or original photographic resolution. Consequently, these acquisition parameters could not be independently verified in the present study. The images were therefore analyzed as published digital images, and their original acquisition conditions were not assumed to be standardized or controlled by the authors of the present work.

For the present computational analysis, each source image corresponding to a given $Pb^{2+}$ concentration was divided into six image patches, yielding a total of 42 image-derived samples. This image-patch extraction procedure was intended to obtain multiple color measurements from different spatial regions of the available images. The resulting patches were subsequently processed to extract color descriptors in the CIELAB color space.

Importantly, the six patches obtained from each source image were not treated as independent experimental replicates, since they originated from the same published image. Instead, they represented spatial subsamples used to characterize the color distribution within each concentration level.

No additional AgNP synthesis, $Pb^{2+}$ detection experiments, or image acquisition experiments were performed in the present study. Accordingly, the dataset was limited to the colorimetric information in the published images, and the analysis focused on evaluating the feasibility of predicting quantitative concentrations from images using machine learning.

### Image Preprocessing and Color Feature Extraction

Each selected image was imported into a Python-based image-processing framework. The relevant sample region was selected as the region of interest (ROI) to minimize the inclusion of surrounding background information. The selected region was then converted from the red, green, and blue (RGB) color representation to the Commission Internationale de l'Éclairage (CIELAB) color space.

Three color coordinates were extracted as quantitative descriptors: L*, representing perceptual lightness; a*, representing the green-to-red color axis; and b*, representing the blue-to-yellow color axis. These descriptors were used to characterize the colorimetric response associated with different $Pb^{2+}$ concentrations. The extracted features served as the input variables for the machine-learning model, while the corresponding reference concentrations were used as the target outputs.

### Machine-Learning-Based Concentration Prediction

A KNN regression model was employed to establish the relationship between the extracted color features and the corresponding $Pb^{2+}$ concentrations. The KNN algorithm estimates the concentration of an unknown sample by identifying neighboring observations in the color-feature space and calculating a prediction based on their associated reference concentrations. Distance-based weighting was applied during model optimization to account for differences in the proximity of neighboring observations.

The model was implemented in Python and incorporated into a graphical user interface (GUI). The application allows users to load a colorimetric image, perform image preprocessing and color feature extraction, and obtain a predicted $Pb^{2+}$ concentration using the trained regression model. This computational workflow was designed to demonstrate the feasibility of quantitatively analyzing published AgNP colorimetric images without requiring new spectroscopic measurements during model inference.



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## Model Evaluation

The predictive performance of the KNN regression model was evaluated using the coefficient of determination ($R^2$), mean absolute error (MAE), and root mean square error (RMSE). $R^2$ was used to assess the agreement between the reference and predicted concentrations, whereas MAE and RMSE quantified the magnitude of prediction errors. Five-fold cross-validation was employed to assess model performance across different data partitions.

The reported performance metrics were calculated from the model evaluation procedure described in this study. Because the dataset consisted of previously published colorimetric images, the resulting performance reflects the model's ability to predict concentrations represented in the analyzed image dataset. It does not, by itself, establish independent experimental validation under newly controlled sensing or imaging conditions..

## RESULTS AND DISCUSSIONS

Representative examples of the published colorimetric images and the corresponding image patches used in this study are presented in Figure 1. The source images were obtained from Khan et al. (2018), and image patches were extracted computationally to generate the image-derived dataset. For each patch, the mean CIELAB coordinates were calculated and used as input features for the machine-learning model. Figure 2 illustrates the relationship between the original colorimetric images, the extracted image patches, and their corresponding numerical color features.

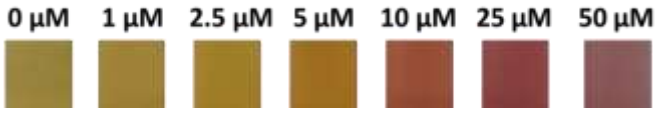



Figure 1. Representative images and color features used in the machine-learning analysis at different $Pb^{2+}$ concentrations, reproduced from Khan et al. (2018).

The predictive performance of supervised machine learning models is strongly influenced by the quality and representativeness of the training dataset. The dataset comprised 42 image-derived samples generated from seven published colorimetric images representing $Pb^{2+}$ concentrations of 0, 1, 2.5, 5, 10, 25, and 50 µM. Each original image was divided into six spatial patches, allowing the extraction of multiple CIELAB color measurements at each concentration level. Since the patches originated from the same source image, they were treated as spatial subsamples rather than independent experimental replicates. Multiple image replicates were included to capture natural variations in color distribution while improving the robustness and generalization capability of the machine learning model.

To convert visual information into quantitative descriptors, each image was converted from the RGB color space to the perceptually uniform CIELAB color space. Unlike RGB coordinates, which are highly dependent on illumination conditions, the CIELAB representation separates luminance (L*) from chromaticity components (a* and b*), providing a more stable numerical description of color variation. The mean L*, a*, and b* values extracted from the region of interest were subsequently employed as input features for machine learning.

Figure 2 shows the extracted CIELAB parameters for each $Pb^{2+}$ concentration. A systematic variation in all three color coordinates was observed as the $Pb^{2+}$ concentration increased. The luminance coordinate (L*) gradually decreased from 55.61 to 37.53, indicating progressive darkening of the AgNP solution. Meanwhile, the a* coordinate shifted toward positive values, reflecting an increase in red coloration, whereas the b* coordinate showed an overall decrease at higher $Pb^{2+}$ concentrations, indicating a reduction in yellow intensity. These continuous chromatic changes are attributed to $Pb^{2+}$-induced aggregation of AgNP, which modifies the LSPR absorption characteristics and consequently alters the perceived solution color.



10.21009/joc.13.03

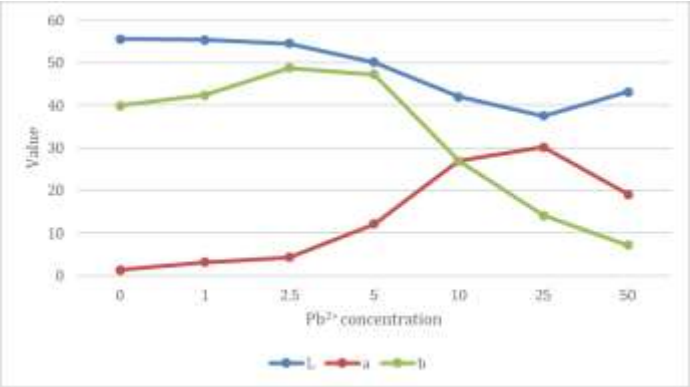



Figure 2. The extracted CIELAB parameters for each $Pb^{2+}$ concentration

The gradual evolution of the CIELAB coordinates demonstrates that $Pb^{2+}$ concentration is strongly correlated with measurable colorimetric features. This continuous relationship provides a suitable feature space for supervised machine learning, as adjacent concentrations exhibit similar yet distinguishable chromatic characteristics, enabling accurate regression without requiring explicit analytical modeling of the underlying optical response.

The extracted CIELAB features were employed to develop quantitative prediction models for $Pb^{2+}$ concentration using the KNN algorithm. Model performance was assessed using five-fold cross-validation to evaluate generalization capability while minimizing overfitting. The predictive accuracy of each model was quantified using the coefficient of determination $R^2$, MAE, and RMSE. As summarized in Table 1, the optimized KNN Regressor model yielded an $R^2$ of 0.9863, indicating that approximately 98.6% of the variance in $Pb^{2+}$ concentration could be explained by the extracted CIELAB features. The corresponding MAE and RMSE values were 0.8073 and 1.9797 μM, respectively, demonstrating low prediction errors throughout the investigated concentration range.

Table 1. Model performance

| Algorithm | Acuration (%) | $R^2$ | MAE | RMSE |
|---|---|---|---|---|
| k-Nearest Neighbors Regressor | 98.63 | 0.9863 | 0.8073 | 1.9797 |

The excellent performance of KNN Regressor can be attributed to the intrinsic characteristics of colorimetric sensing (Tiandho et al., 2026). Since neighboring $Pb^{2+}$ concentrations generate gradual color transitions rather than abrupt spectral changes, samples with similar CIELAB coordinates naturally occupy neighboring positions within the multidimensional feature space. KNN Regressor exploits this local similarity by estimating unknown concentrations from nearby training samples, enabling accurate interpolation without assuming a predefined mathematical relationship between color and concentration. Consequently, the algorithm effectively captures the nonlinear behavior associated with AgNP aggregation during $Pb^{2+}$ detection.

To evaluate the practical applicability of the developed framework, the trained KNN model was used to predict the $Pb^{2+}$ concentration of unknown colorimetric images. The predicted concentrations were subsequently compared with their corresponding reference values obtained from the experimental dataset.

As presented in Table 2, the proposed framework demonstrated excellent agreement between predicted and reference concentrations across the investigated range. For concentrations between 1 and 50 μM, the predicted values matched the reference concentrations exactly, whereas only a slight deviation (0.16 μM) was observed in the blank sample (0 μM). This small deviation corresponds to a full-scale error of only 0.32%, indicating that the developed framework maintains high prediction accuracy even at the lowest concentration level.

Table 2. Comparison between model prediction results and actual data

| Actual Concentration (μM) | Prediction Concentration (μM) | Error |
|---|---|---|
| 0 | 0.16 | 0.32% |
| 1 | 1 | 0% |
| 2.5 | 2.5 | 0% |
| 5 | 5 | 0% |
| 10 | 10 | 0% |
| 25 | 25 | 0% |
| 50 | 50 | 0% |



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The slightly higher prediction error observed at the blank sample can be attributed to the inherent variability of digital image acquisition, including subtle illumination fluctuations, sensor noise, and minor color heterogeneity within the AgNP solution. Because the blank sample shows the smallest chromatic difference relative to neighboring concentrations, even minor variations in pixel intensity may affect the extracted CIELAB values. Nevertheless, the resulting prediction error remained negligible compared with the investigated concentration range, demonstrating the robustness of the proposed image-based sensing approach.

Overall, these results confirm that quantitative $Pb^{2+}$ determination can be achieved directly from colorimetric images without the need for spectroscopic instrumentation. The combination of AgNP-based colorimetric sensing, CIELAB feature extraction, and KNN regression enables rapid, accurate, and computationally efficient concentration prediction using only digital photographs.

To facilitate practical implementation, a GUI was developed using the Python Tkinter framework, as illustrated in Figure 3. The application integrates image loading, CIELAB feature extraction, machine learning inference, and result visualization into a single workflow. After a user uploads a colorimetric image of an AgNP sample, the software automatically extracts the corresponding color features and predicts the $Pb^{2+}$ concentration using the trained KNN regression model.

The complete prediction process is executed within a few seconds on a conventional personal computer, demonstrating the computational efficiency of the proposed framework. Compared with conventional UV–Vis spectrophotometric analysis, the developed software eliminates the need for expensive laboratory instrumentation while maintaining high predictive accuracy. This capability highlights the potential of integrating computer vision and machine learning with AgNP-based colorimetric sensing to develop portable, low-cost, and user-friendly platforms for real-time environmental monitoring of lead contamination.




Figure 3. GUI for $Pb^{2+}$ detection using machine learning

Most previously reported AgNP-based colorimetric sensors rely on qualitative visual inspection or quantitative analysis using UV–Vis spectrophotometry. Although these approaches provide reliable analytical performance, they generally require dedicated laboratory instrumentation, limiting their suitability for rapid field deployment. In contrast, the proposed framework directly converts digital colorimetric images into quantitative $Pb^{2+}$ concentrations through machine learning, thereby replacing conventional spectroscopic measurements with computational image analysis. The KNN algorithm accurately models the nonlinear relationship between colorimetric response and $Pb^{2+}$ concentration without requiring explicit physical calibration equations. These characteristics make the proposed framework particularly attractive for smartphone-assisted environmental sensing, where portability, simplicity, and low operational cost are essential (Bhatt et al., 2024).

Nevertheless, several limitations should be acknowledged. The image dataset employed in this study was derived from published experimental images, and therefore, future studies should validate the proposed framework using independently acquired datasets under diverse illumination conditions and camera systems. Expanding the dataset and incorporating advanced machine learning models, such as convolutional neural networks or vision transformers, may further improve prediction robustness and enable broader applications for quantitative colorimetric sensing of environmental pollutants.



10.21009/joc.13.03

## CONCLUSIONS

This study successfully developed and validated a low-cost, high-precision predictive framework using computer vision and machine learning to quantify $Pb^{2+}$ concentration from digital images of AgNP colorimetric sensors. By replacing expensive conventional laboratory hardware with a Python-based pipeline, raw digital photos were efficiently mapped into the device-independent CIELAB color space to track L* a* b* variations caused by nanoparticle aggregation. The optimized KNN regressor demonstrated exceptional predictive stability. The deployment of this model into a functional, standalone desktop GUI proves that sophisticated heavy metal environmental diagnostics can be decentralized into a real-time, user-friendly, and accessible tool for fieldwork.

## ACKNOWLEDGEMENTS

This study was funded by the Directorate General of Research and Innovation, Ministry of Higher Education, Science, and Technology, Republic of Indonesia, through the Program Hilirisasi Riset Prioritas – Pengujian Model dan Prototipe (Grant No. 439/UN50/M/PP/2026).



10.21009/joc.13.03

## REFERENCES

Bhatt, S., Kumar, S., Gupta, M.K., Datta, S.K. & Dubey, S.K. (2023). Colorimetry-based and smartphone-assisted machine-learning model for quantification of urinary albumin. Measurement Science and Technology, 35, 015030. https://doi.org/10.1088/1361-6501/acfd4c

Bouida, L., Rafatullah, M., Kerrouche, A., Qutob, M., Alosaimi, A. M., Alorfi, H. S., & Hussein, M. A. (2022). A review on cadmium and lead contamination: Sources, fate, mechanism, health effects, and remediation methods. *Water, 14*(21), 3432. https://doi.org/10.3390/w14213432

Csavina, J., Field, J., Taylor, M. P., Gao, S., Landázuri, A., Betterton, E. A., & Sáez, A. E. (2012). A review on the importance of metals and metalloids in atmospheric dust and aerosol from mining operations. *Science of the Total Environment, 433*, 58–73. https://doi.org/10.1016/j.scitotenv.2012.06.013

Khan, N. A., Niaz, A., Zaman, M. I., Khan, F. A., Nisar-ul-Haq, M., & Tariq, M. (2018). Sensitive and selective colorimetric detection of $Pb^{2+}$ by silver nanoparticles synthesized from Aconitum violaceum plant leaf extract. *Materials Research Bulletin, 102*, 330–336. https://doi.org/10.1016/j.materresbull.2018.02.050

Lanphear, B., Navas-Acien, A., & Bellinger, D. C. (2024). Lead poisoning. *The New England Journal of Medicine, 391*(10), 911–923. https://doi.org/10.1056/NEJMra2402527

Roto, R., Mellisani, B., Kuncaka, A., Mudasir, M., & Suratman, A. (2019). Colorimetric sensing of $Pb^{2+}$ ion by using Ag nanoparticles in the presence of dithizone. *Chemosensors, 7*(3), 28. https://doi.org/10.3390/chemosensors7030028

Siame, T., Muzandu, K., Mulenga, K. K., & Dzombe, C. B. (2025). Lead-contaminated groundwater exposes residents to health risks in Makululu, Zambia. *Journal of Water and Health, 23*, 615-629. https://doi.org/10.2166/wh.2025.343

Sudarman, F., Shiddiq, M., Armynah, B., & Tahir, D. (2022). Silver nanoparticles (AgNPs) synthesis methods as heavy-metal sensors: A review. *International Journal of Environmental Science and Technology, 20*, 6393–6416. https://doi.org/10.1007/s13762-022-04745-0

Tiandho, Y., Muslihati, A., Septiani, N.L.W., Afriani, F., Jonuarti, R., Suprijadi, S. & Yuliarto, B. (2026). Integrated plasmonic–machine learning system for the rapid and selective detection of Escherichia Coli using Ag@ Au nanoparticles. Journal of Materials Science, 2026. https://doi.org/10.1007/s10853-026-13963-7

World Health Organization. (2026, June 10). Lead poisoning. https://www.who.int/news-room/fact-sheets/detail/lead-poisoning-and-health

Yu, L., Sun, L., Zhang, Q., Zhou, Y., Zhang, J., Yang, B., Xu, B., & Xu, Q. (2022). Nanomaterials-based ion-imprinted electrochemical sensors for heavy metal ions detection: A review. *Biosensors, 12*(12), 1096. https://doi.org/10.3390/bios12121096



10.21009/joc.13.03