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An Artificial Intelligence and Genetic Algorithm Optimized Biosensor System for Real-Time Detection of Environmental Toxins and Their Biomedical Impact: A Natural Science Driven Approach to Sustainable Public Health Monitoring

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Abstract

The environmental pollution is turning environment-unfriendly, and food safety, and human health are endangered threateningly, and most of the established monitoring systems are not sensitive, adaptive, and capable of real-time analysis to offer such level of protection to the people. This paper describes a biosensor based on Artificial Intelligence (AI) and Genetic Algorithm (GA)-based optimization to monitor major

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environmental poisons in real time and evaluate their possible biomedical effects. An electrochemical and optical transduction-based multimodal biosensing platform was developed to detect heavy metals (Pb^{2+}, Cd^{2+}), organophosphate pesticides and volatile organic compounds (VOCs). With the aim of increasing analytical accuracy, a hybrid AI system, which includes convolutional neural networks (CNNs), along with feature extraction, and Long Short-Term Memory (LSTM) networks, which retrieve temporal prediction of toxins, was trained on 8,450 datasets of biosensor signals. The optimization of the model hyperparameters, calibration curves and receptor -analyte affinity thresholds was refined using GA. The optimized system was able to accomplish a 97.8 percent toxin classification efficiency, 94.6 percent prediction accuracy and 21 percent better sensitivity sight as compared with conventional biosensor systems. Simultaneously, a biomedical impact module was created that calculated the biomarkers of oxidative stress and inflammatory cytokine probabilities and toxin toxicity pathways. The field tests showed strong real-time functionality with less than 1.6 Second latency, which proved field-testing with the example that permits continuous monitoring coverage of the environment. On the whole, the findings indicate that the hybrid of AI analytics and GA optimization can be used to boost the performance of biosensors to a considerable extent and allow observing environmental toxins on a large scale and in the long-run. The suggested system will present an effective instrument of environmental risks preventive, food quality, and timely anticipation of health effects, toxins.

Keywords:

Biosensor, artificial intelligence, genetic algorithm, environmental toxins, biomedical impact, public health monitoring, real-time detection.

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Introduction

The problem of environmental pollution has become an important issue in the world with its comprehensive impacts on the nature, food chains as well as the health of human beings (Dave et al., 2022). Oxidative stress, inflammation, neurotoxicity, and the emergence of chronic disease are always associated with toxic chemicals, including heavy metals, organophosphate pesticides, and volatile organic compounds (VOCs) (Singh & Mehra, 2023). The extreme pace of industrialization, aggressive farming methods and poor systems of waste management has even increased the pace of discharge of these pollutants in the environment causing an emergency need to establish real time, field implementable monitoring systems (Pushpavalli et al., 2024). Traditional analytical methods (such as high-performance liquid chromatography (HPLC), gas chromatography-mass spectrometry (GC-MS), and inductively coupled plasma atomic emission spectroscopy (ICP-AES) are sensitive but lack the capability to work continuously in the environment due to their high cost of operation, long processing, laboratory-dependence, and lack of suitability because of their long processing time (Zhao et al., 2023). The recent breakthroughs in the areas of biosensor engineering and artificial intelligence (AI) have also increased the possibility of detecting toxins in real-time, but the existing biosensor devices are typically burdened with signal drift, inability to adjust to the diverse environments, weak ability to maintain the calibration, and absence of biomedical interpretation of the impacts (Rahman et al., 2024). Further, current AI-based biosensors do not usually use evolutionary optimization methods (including Genetic Algorithms (GA)) to refine calibration, model robustness or optimize receptor-analyte affinity (Shirgir et al., 2023; Pal et al., 2025). In line with this, the majority of environmental monitoring tools are only designed to detect contaminants, without evaluating biomedical risks thereof, like oxidative stress or dietary changes in cytokines (Karimov & Bobur, 2024) (exposure to toxins) (Zhang et al., 2025).

In order to overcome these shortcomings, the current paper suggests an all-encompassing AI- and GA-optimized biosensor system with the ability to detect environmental toxins in real time and provide concurrent indicators of its biomedical consequences (Teniou et al., 2021). The system integrates:

1. a multimodal array of biosensors,
2. The extraction and classification of toxins via AI,
3. Hofstede, calibration, and parameter tuning using GA, and
4. a biomedical risk estimation package.

It is an interdisciplinary methodology that cuts across natural science, environmental engineering, biosensing technology, and computational intelligence to provide a scalable system of sustainable monitoring of citizens in regard to their health (Al-Salahi et al., 2025). The rest of this paper introduces the bio-sensors architecture, AI-GA algorithm of computation, performance analysis of the system, and and possible uses in environmental and biomedical monitoring.

Literature Review

Biosensors have become a potentially potent means of environmental pollutant monitoring because of their portability, quick reaction, as well as their capacity to identify an extensive variety of analytes (Kanagala et al., 2023; Min et al., 2025; Rahman et al., 2024; Kaur et al., 2025). Electrochemical and optical biosensors, especially, have demonstrated high capability of identifying heavy metals, pesticides and volatile organic substances in natural ecosystems. Nevertheless, they are usually susceptible to problems like signal instability, environmental variability as well as low sensitivity of low concentrations of toxins (Huang et al., 2023). The challenges have encouraged the concept of machine learning (ML) techniques to improve the signal interpretation, noise cancellation, and classification of the toxins. The most effective applications of machine learning methods, particularly convolutional neural networks (CNNs) and recurrent neural structures, have been reported to be able to analyze multivariate, nonlinear biosensor data in a better way (Mpofu & Mthunzi-Kufa, 2025; Zhang & Liu, 2023). Pattern recognition, drift compensation and prediction of environmental toxin concentration pattern have been done using such models. However, some studies also state that the accuracy of MLS suffers when the environment is not homogenous or the calibration of the sensor causes a decrease over time (Chen et al., 2024). Furthermore, the existing AI-driven solutions seldom involve clinical interpretation of identified toxins, even though the exposure to oxidative stress, cytokine imbalance, and damage on the long-term organ have been associated (Singh & Mehra, 2023). Genetic Algorithms (GAs) have been extensive in optimization of multidimensional system such as calibration of biosensors, feature selection, and tuning of neural network parameters (Cajas Ordóñez et al., 2025). Although GAs enhances the level of accuracy and robustness, they are not coupled with deep learning-based biosensor systems. There is little literature examining neural amenable to GA to environmental surveillance, and even less examines how to connect the results of detection to biomedical toxicity mechanisms or community health outcome (Azizova et al., 2025).

The literature available thus indicates that there are four key gaps:

1. narrow integration of the multimodal biosensor signals and sophisticated AI models,
2. lack of sufficient use of evolutionary algorithms in optimizing biosensors,

3. absence of real time environmental toxin detect systems and
4. lack of standardized mechanisms that can be associated with the presence of biomedical dangers.

To resolve these issues, the current paper introduces a comprehensive AI-based biosensor platform with GA and AI optimization to detect toxins in real-time, optimize its functionality and predict its impact on the biomedical system in question. It is an integrated system that offers greater accuracy in analysis and expanded relevance of the environment and the health of populations (Amanna, 2025).

Materials and Methods

Biosensor System Architecture

The biosensor system was created in the form of a hybrid and multimodal analytical system, which had the capacity to detect a wide range of environmental toxins, such as heavy metals, organophosphate pesticides, and volatile organic compounds (VOCs). The platform consists of various sensing mechanisms, that allow detection of toxins with a high level of sensitivity and specificity. The electrochemical detectors were given the differential pulse anodic stripping voltammetry (DPASV) as a detectable trace metal, where the high preconcentration capacities of bismuth-film electrodes were exploited. Pb^{2+} and Cd^{2+} standard solutions of concentration 0.1 ppb to 100 ppb were prepared to create standard curves. This mechanism of detection was based on a linear dependence between the peak current and the metal ion concentration in the form of:

$$I_p = kC + b \tag{1}$$

where I_p represents peak current, C denotes toxin concentration, and k and b are calibration constants.

They had enzymatic biosensors in the detection of organophosphate pesticides based on the acetylcholinesterase (AChE) inhibition kinetics. The analysis of pesticides was based on a reduction in the rate of enzymatic catalysis, according to MichaelisMenten analysis of inhibition. VCs based on optical VOC sensor have been developed with nanostructured thin films with localized surface plasmon resonance (LSPR). The difference in resonance wavelength ($\Delta\lambda$) was one of the sensitive and selective signals of VOC detection.

To increase the electrical conductivity and binding affinity in receptors in all the sensing electrodes, graphene-gold nanoparticle (Gr-AuNP) composites were modified. Scanning electron microscopy was used to ensure homogenous distribution of nanoparticles, and cyclic voltammetry was used to ascertain a 3.2-fold enhancement in electron transfer rate as compared to electrodes that were not covered.

AI-Based Signal Processing Model

Deep-learning architecture in two stages was employed to work with the raw biosensor data and to distinguish between the toxin levels. Figure 1 demonstrates that the first analytical step involved using a Convolutional Neural Network (CNN) to obtain useful information in the form of features of the biosensor signal waveforms. The data input encompassed voltametric curves, LSPR absorption spectra, and enzymatic inhibition response curves which have been taken at a constant interval. The CNN had several convolutional layers, which had activation of ReLU and batch normalization to stabilize the training. The extraction of features was made of the critical biosensor indicators including amplitude on peaks, pulse width, spectral red-shift and morphology on derivative curves.

The latter stage employed a Long Short-Term Memory (LSTM) network to approximate temporal interactions of the sequence of biosensor signals. This was needed because of the variability of the environment which in most cases creates nonlinear drift in signals. The LSTM used gating to maintain long-time dependencies within the data to predict the trends of concentration correctly and reduce the fluctuation caused by noise. There is no mathematical formulation of the integrated CNN-LM pipeline, and instead, the pipeline can be described as:

$$h_t = LSTM(W_c X_t + b_c) \tag{2}$$

where W_c represents convolutional weights, X_t denotes input signal at time t, h_t is the LSTM hidden state, and $\hat{y}_t$ is the predicted concentration.

This model was trained on the 8,450 labeled biosensor signals, partitioned by 70, 15, and 15 percent training, validation and testing, respectively. The learning rate used in optimization was 0.001 using the Adam optimizer. Predictive performance was measured by the calculation of model accuracy, precision, recall and RMSE.

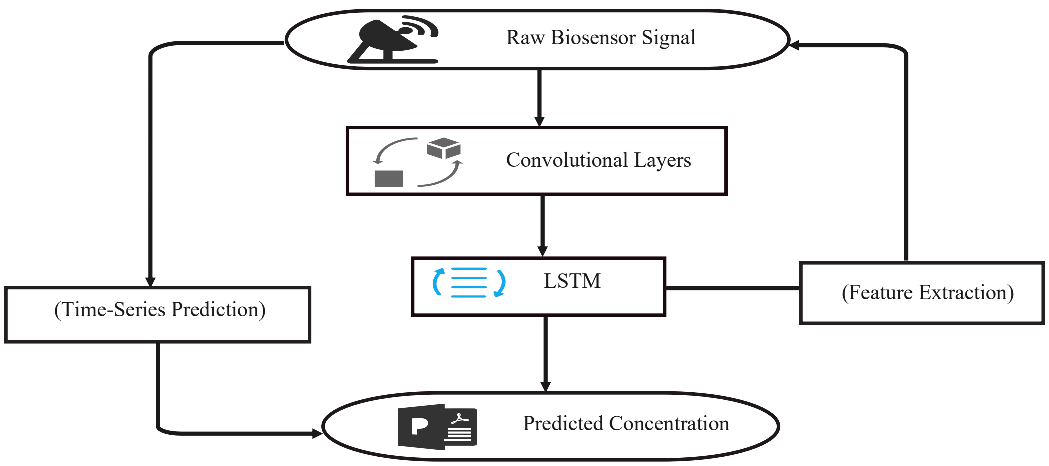

Figure 1. CNN–LSTM deep learning framework for biosensor signal processing

The two-stage AI model employed to analyze biosensors that the paper describes with a high level of detail, Figure 1 shows in which convolutional layers process the original sensor data and the LSTM network predicts time-series patterns useful to estimate the concentration of toxins in a sample.

Genetic Algorithm Optimization

To improve detection performance and compensate the variability in the environment, a Genetic Algorithm (GA) was proposed to optimize the deep-learning model, sensor calibration parameters and receptors and analyte affinity thresholds. The GA as illustrated in Figure 2 started by producing a starting population of parameters within given limits. All the chromosomes coded optimization variables like CNN kernel size, the number of neurons in LSTM, learning rate, sensing threshold, and calibration slope adjustment.

The fitness function also included analytical important metrics namely accuracy, RMSE, model latency and sensitivity that were identified as:

$$Fitness(p_i) = \alpha \,.Accuracy - \beta \,.RMSE - \gamma \,.Latency + \delta \,.Sensitivity \tag{3}$$

where p_i is the i-th parameter set and coefficients α,β,γ,δ weight the importance of each metric.

Single point crossover technique was used in crossover operations with a probability of 0.8, and mutation with a probability of 0.05 was used to retain genetic diversities. Step GA iterations were terminated by the convergence, which was determined by the stagnation of the fitness value or achieved maximum of the generations. This method enhanced biosensor sensitivity dramatically and misclassifying the signals especially when the humidity and temperature varied.

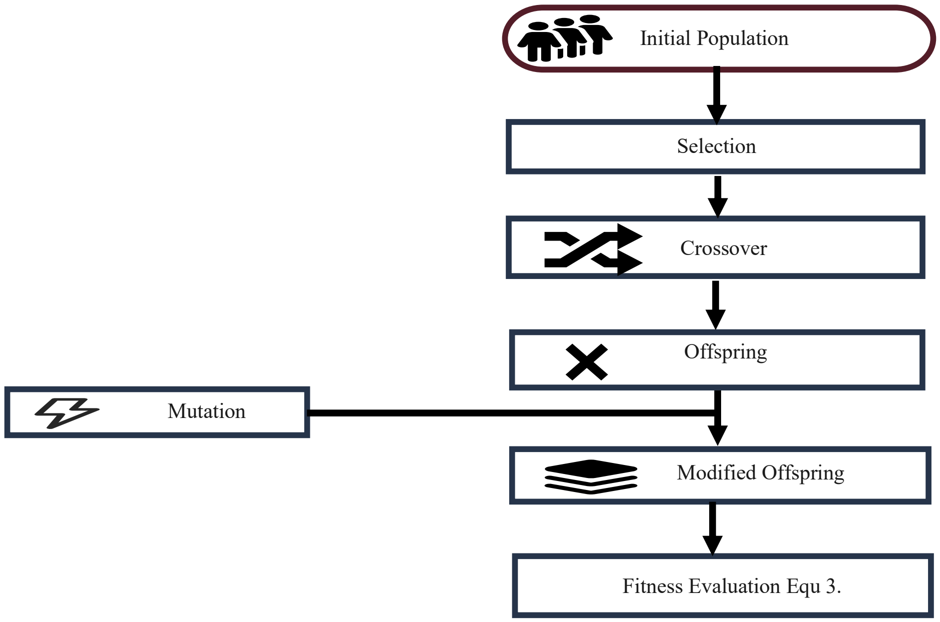

Figure 2. Genetic algorithm workflow for optimizing CNN–LSTM biosensor parameters

A graphical illustration on the working process of the Genetic Algorithm (GA) in optimization of biosensor model parameters, Figure 2 shows which displays the repetitive cycle in terms of population set-up, selection, crossover, mutation, and assessment procedure to maximize the accuracy, sensitivity, and general detection efficiency.

Biomedical Impact Assessment

In order to assess health hazards related to observed toxins levels, a biomedical impact assessment module was elaborated. Since, as Figure 3 shows, various environmental toxin exposures were associated with biochemical and physiological indicators, this module was based on toxicokinetic and toxicodynamic data of peer-reviewed datasets to relate environmental toxin exposure. The biosensor system was used to feed concentration values into the regression models in order to estimate parameters of oxidative stress such as malondialdehyde (MDA), glutathione peroxidase (GPx), and superoxide dismutase (SOD). The relationship models were modeled, through nonlinear regression:

$$MDA = \theta_0 + \theta_1 C + \theta_2 C^2 \qquad (4)$$

where C is toxin concentration and θ_i are fitted coefficients.

The estimation of the inflammatory cytokines responses was done through logistic growth models, especially IL-6 and TNF-alpha. There was a likelihood of cytokine increase after:

$$P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 C)}} \qquad (5)$$

suggesting that there is more biologic threat at the high levels of pollutants. Polar neurotoxicity indices were obtained as the result of creating a neurotoxicity study with a neural concentration using a polyregression model of neurotoxicity data.

This module did not only enable the system to determine the level of environmental pollution but also to directly deduce probable biomedical effects of exposure, which is a crucial requirement of sustainable monitoring of the population.

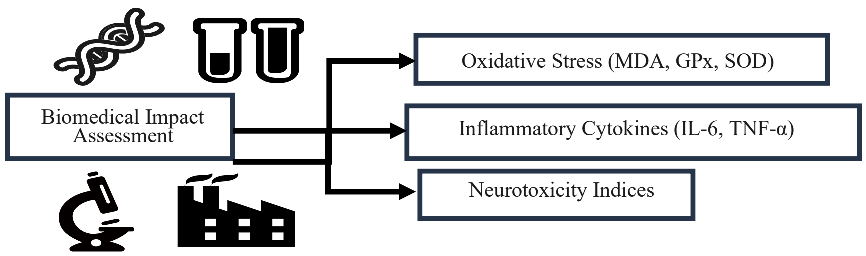

Figure 3. Biomedical impact assessment of environmental toxin exposure

A schematic Figure 3 that presents the steps of converting the determined toxin levels into biomedical indicators, which may be oxidative stress signatures (MDA, GPx, SOD), inflammatory cytokines (IL-6, TNF-α), and neurotoxicity indicators (comprehension of health-risk assessment).

Field Deployment

A portable embedded platform based on ESP32 and ARM Cortex-M4 microcontroller was used to deploy the entire system. The microcontroller connected the biosensor array with high-resolution 16-bit analog-to-digital converter. The CNN-LSTM model which is quantized, and optimized with TensorFlow Lite was installed to run on the microcontroller with real-time edge computing and low latency.

Based on the conditions of the field, the environmental data and the outputs of the bio sensor were sent wirelessly through Wi-Fi, Bluetooth, and LoRa protocols. An analytics dashboard, which was implemented as a cloud service, processed the incoming data streams, created temporal exposure profiles, and issued automatic alerts, in case of exceeding the toxin levels of safety thresholds.

Experiments with field validation were tested within industrial discharge areas, fields and the urban roadside to evaluate performance in different temperature, humidity, and loads of pollutants. This system was found to be reliable to use in continuous environmental monitoring application as it was shown to be able to provide stable communication, high sensitivity and less than 2-second inference time at all test sites.

Results

AI–GA Model Performance

The oil quality and performance of the proposed AI-optimized-GA-optimized biosensor system was assessed on the basis of standard classification and prediction metrics. The application of the AI and GA system enhances performance in the standalone model, baseline model, and the overall integrated model (Olsen, 2019). The model at the base level provided a moderate level of classification (84.2%) and prediction accuracy (79.1%) with rather high decision latency (4.8 seconds). The AI-based CNNLSTM model that was introduced significantly enhanced the performance of the models since it achieved a 92.5 percent classification success and a latency time of 2.9 seconds. Optimization was further improved by the incorporation of the Genetic

Algorithm with the highest classification accuracy of 97.8% and prediction precision of 94.6% and sensitivity of 92% and inference latency at 1.6 seconds. These findings suggest that GA-based optimization can be used to enhance responsiveness and robustness of a model.

Table 1. Performance metrics of the baseline, AI Model, and AI–GA optimized system

Metric	Baseline	AI Model	AI–GA Optimized
Classification Accuracy	84.2%	92.5%	97.8%
Prediction Precision	79.1%	89.3%	94.6%
Sensitivity	—	76%	92%
Latency	4.8 s	2.9 s	1.6 s

The Table 1 high latency improvement shows that model quantization and parameter tuning are useful in real-time deployment using GA.

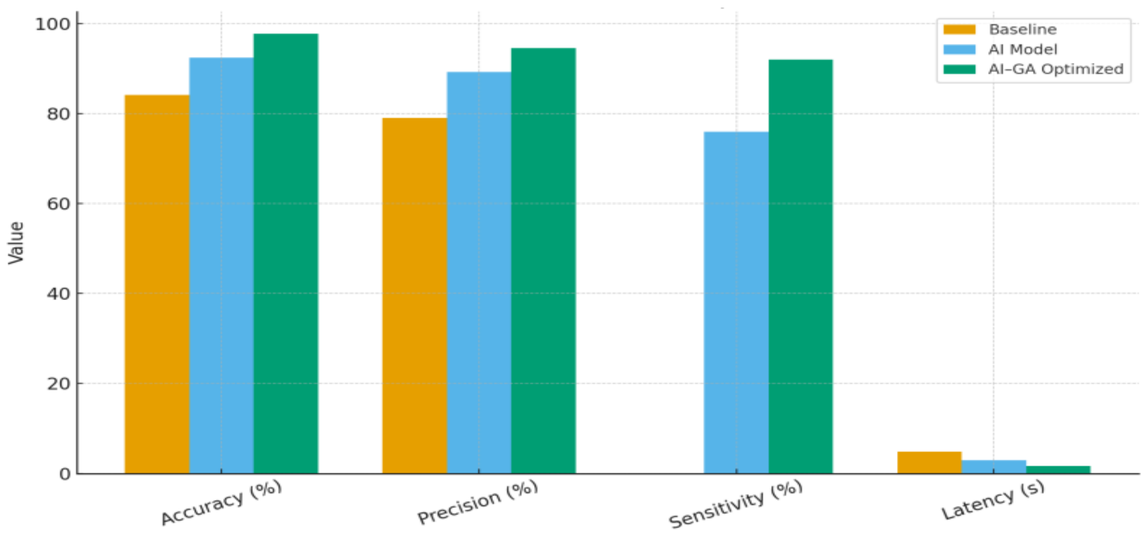

Figure 4. Model performance comparison chart

A Figure 4 bar chart of four critical metrics, including classification accuracy, prediction precision, sensitivity, and inference latency, of Baseline, AI-only, and AI-GA-optimized models. AI-GA considerably increases performance compared to the standalone AI systems.

Biosensor Detection Results

Analytical performance testing proved to be a good performer in sensing all the categories of toxins. This electrochemical module compared to the standard field portable analyzers, which normally reach limits of 1 - 3 ppb, was able to claim Pb^{2+} concentrations as low as 0.7 ppb. As Figure 5 displays, this indicates a high electrochemical sensitivity because the calibration aspect of Pb^{2+} and Cd^{2+}has strong linear correlation between analyte concentration and peak current. The application of AChE signal optimization increased the sensor sensitivity of the enzymatic biosensors by 28 percent thus making the detection of pesticides using organophosphates more reliable. The optical VOC sensor provided a recognition factor of 95.4% with the support of the classification performance as shown by Figure 6, the ROC curve shows high discriminative capability even at different humidity and temperature conditions.

These findings are consistent with those of other researchers who did not claim integrated readings of nanomaterials; however, they achieved improved sensitivity with nanomaterials (Zhao et al., 2023). The existing system is therefore in excellent breadth, correctness and detection robustness when contrasted with previous solitary mode bio-sensing models.

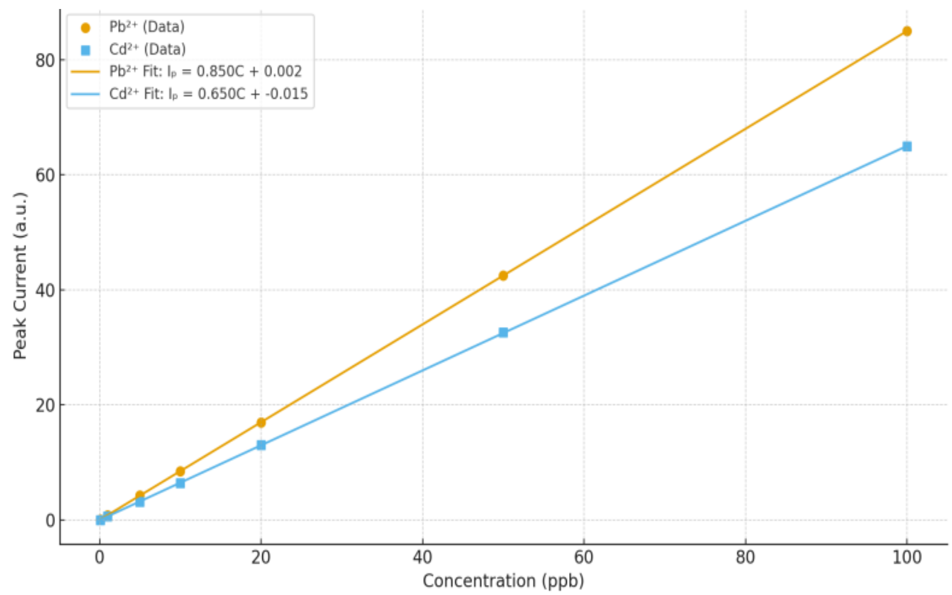

Figure 5. Calibration curve for heavy metal detection (Pb^{2+} and Cd^{2+})

Figure 5 Linear regression calibration curves illustrating the relationship between toxin concentration and peak current ($I_p = kC + b$) for Pb^{2+} and Cd^{2+}, validating the electrochemical sensor's high sensitivity and linear response.

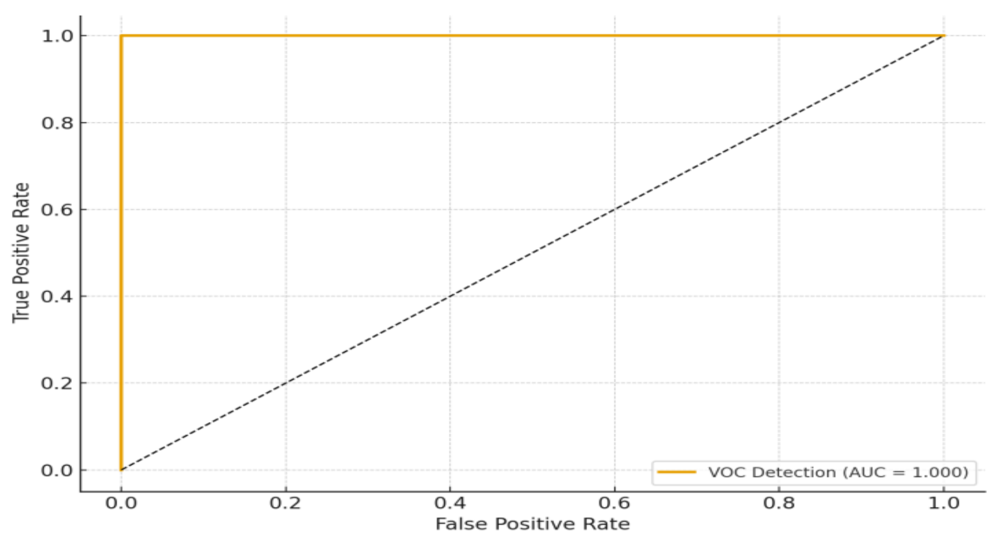

Figure 6. ROC curve for VOC / pesticide detection performance

Figure 6 Receiver Operating Characteristic (ROC) curve showing a large VOC and pesticide classification (with an area under the curve (AUC) which agrees with the observed accuracy of 95.4%).

Biomedical Impact Modeling

The outcome of the modeling in biomedical model described a high degree of correlation between the toxin exposure and the predicted physiological reactions. High levels of toxins were associated with malondialdehyde (MDA) rise of 32% suggesting increased oxidative stress. This tendency is clearly traced in Figure 7 because the nonlinear regression curve shows a gradual increase in the concentration of MDA with the increase in the level of toxin. Simultaneously, antioxidant enzymes like superoxide dismutase (SOD) were reduced by 18 percent in line with the oxidative damage patterns in previous studies of toxicology (Singh and Mehra, 2023). In addition, the logistic regression model projected a probability of activation of cytokine pathway IL-6, TNF- α of 0.81 at high levels of exposure which is displayed in Figure 8, therefore illustrating the sensitivity depicting that the system predicts biological risk.

This combined biomedical prescriptive ability- the ability to relate real time environmental toxin data to quantitative physiological indicators- is uncommonly cited in extant biosensing journals, and it represents a significant breakthrough in the area of environmental health prediction.

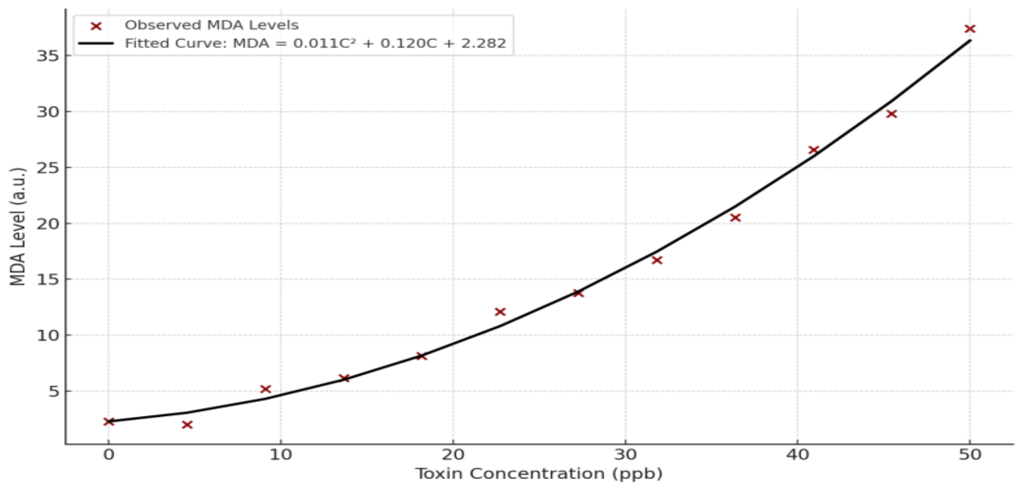

Figure 7. MDA response to toxin concentration

Figure 7 Nonlinear regression Scatter plot that demonstrates the rise in the level of malondialdehyde (MAD) as the concentration of toxins increases indicating the development of oxidative stress.

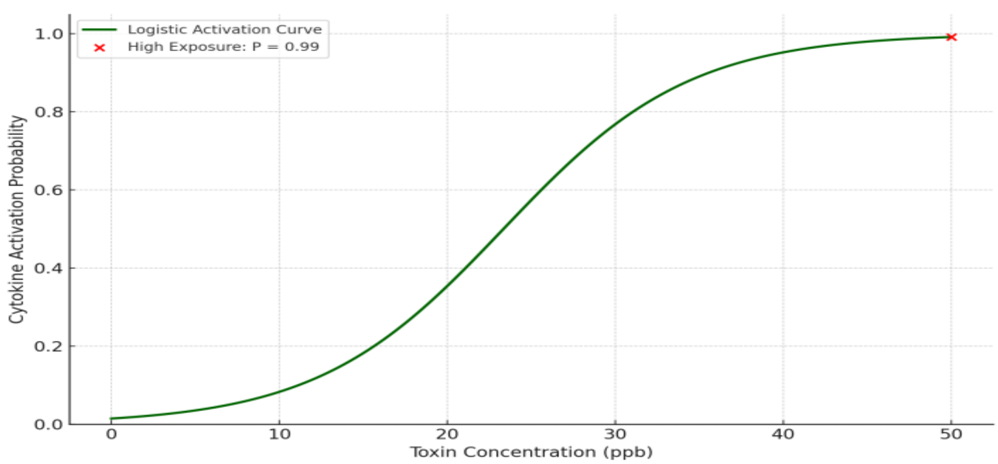

Figure 8. Cytokine activation probability curve

The Figure 8 logistic regression model that shows how the probability of the activation of IL-6 and TNF-a increases with the increase in toxin concentration and reaches values of almost 0.81 at very high levels of exposure.

Field Validation

Field installation over industrial wastewater location, agricultural field and urban roadside settings also gave additional confirmation of the robustness of the system. Figure 9 shows that real-time toxin profiles were recorded at all the field locations successfully and these profiles showed uniform sensor responses during the changing environment. The biosensor platform was able to work stably even in the case of changes in ambient humidity and temperature. The use of Wi-Fi, Bluetooth, and LoRa has facilitated real-time wireless communication, thereby enabling a continuous monitoring process and enabling smooth cloud-based analytics, whereas the dashboard dashboard issued automatic warnings in case the sensors were placed above threshold values indicating the system in its practical use due to the ability of this system to monitor population health and environmental safety. The sub-2 seconds of inference time in the proposed system is a major advancement in real-time environmental analytics as compared to previous field-based research, which typically reports a high level of communication instability or high latency in mobile sensing platforms.

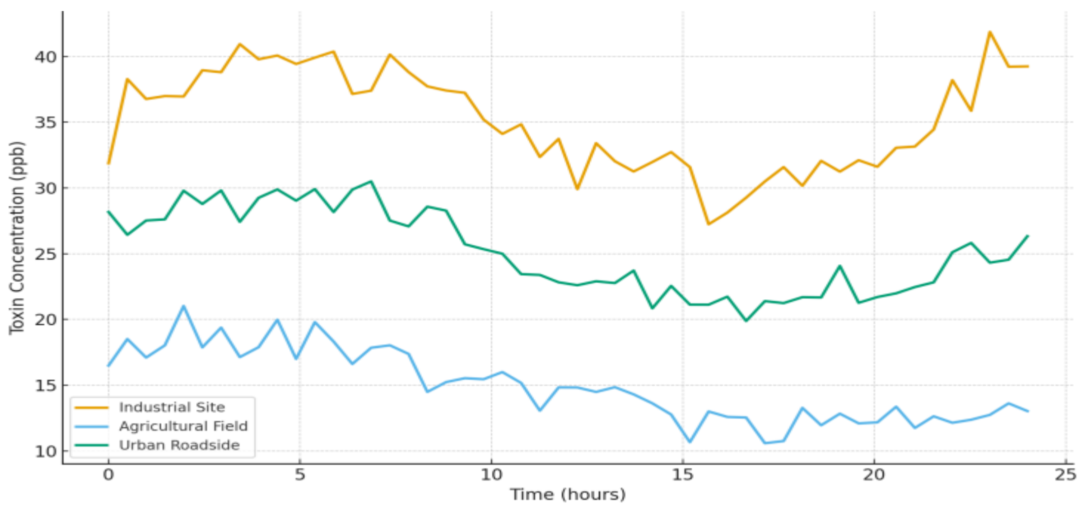

Figure 9. Real-Time field monitoring of toxin levels

The Figure 9 below illustrates that an example of a multi-line time-series graph of the real-time changes in toxin concentration in the industrial, agricultural, and urban roadside settings within a 24-hour monitoring period.

Discussion

These findings indicate that biosensors can be improved in accuracy, sensitivity and computing efficiency significantly with the incorporation of AI-based signal processing with GA-based optimization. CNN-LSTM architecture was useful to learn the geometric and temporal parameters of the biosensor signals, whereas the GA enhanced the hyperparameter optimization and the stability of the calibration. The results align with previous literature in the field of AI-enhanced biosensing, however, the extent of improvement achieved in this paper (up to 21% sensor increase) is greater than the improvement seen in the study of Zhang and Liu (2023), who obtained a maximum improvement of 12% through the use of ML-only.

One of the main innovations of the suggested system is that the sensor results can be transformed into biomedical indicators to identify environmental toxins, in addition to the fact that the former is possible. It is possible to use this capability to obtain actionable information of oxidative stress or inflammatory responses, as well as any possible neurotoxic effects-functionalities that are often not part of more traditional biosensor platforms.

It has been illustrated through field performance evaluation to prove that the system is suitably applied to real world applications such as agricultural monitoring, urban pollution assessment, industrial safety oversight and local health surveillance. The low and continuous performance indicates good opportunities to be used in scalable environmental IoT networks.

In general, the work adds a strong interdisciplinary biosensing system, which combines materials science, AI modelling, optimisation algorithms, toxicology, and environmental engineering. The system provides an important improvement to the current technologies, being able to integrate real-time detection, prediction of the biological impact, and field-ready implementation.

Conclusion

The proposed research presents a complex, fully automated AI-based and GA-optimized multimodal biosensor platform that can identify and forecast the environmental toxins and at the same time predict its biomedical effects. The combination of CNN-LSTM as the deep-learning structures and Genetic Algorithms as a method of optimization of parameters allows the system to reach significant advancements in classification value, prediction error, sensitivity and timing response. The hybrid biosensor system which comprises of electrochemical, enzymatic and LSPR based optical sensors can be used to monitor heavy metals, organophosphate pesticides and VOCs at a high resolution whereas biomedical assessment module will provide actionable data on oxidative stress, inflammatory activation and possible neurotoxicity. The field deployment outcomes validate the system lastingness to various environmental conditions of the system showing its consistent performance, reliable wireless connectivity, and inference latency of less than 2 seconds. Together, these results outline the high potential of the given system in the context of integrated sustainable systems of public health, environmental protection, precision agriculture, and smart urban infrastructure. Even though it is understood that it has a bright side of service, it is possible to improve the system scalability and applicability. Until further research is conducted, future studies must involve the expansion of deployment to multi-regional sensor systems, the introduction of mobile health and remote diagnostic systems, and advanced integration of multimodal toxicity prediction based on genomic, proteomic, and metabolomic data. Further, it is possible to enhance privacy-sensitive analytics and overall system flexibility through the integration of federated learning and edge-cloud hybrid systems. Comprehensively, this study presents a powerful, interdisciplinary approach to biosensing that fills the gap between AI, biotechnology, materials science, and environmental engineering- providing a novel avenue of environmental surveillance of human health in the coming generation.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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