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REAL-TIME SOIL CONTAMINANT MONITORING USING MICROBIAL BIOSENSORS AND SUPPORT VECTOR MACHINE

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Continuous real-time monitoring of soil contamination is imperative for environmental safeguarding. Traditional laboratory-based analyses, however, are slow, expensive, and not viable for continuous on-site field work. In this work, we propose a hybrid soil monitoring strategy that combines microbial biosensors with a Support Vector Machine (SVM) classifier for quick detection of contaminants. Specifically modified Escherichia coli bacteria are engineered to react specifically to lead (Pb^{2+}), mercury (Hg^{2+}), and organophosphate compounds. They do this by generating electrical bio-signals with voltages ranging from 0.2 V to 1.5 V at contaminant concentrations above 50 ppm. The bio-signals are converted to digital form using a 12-bit ADC at a 1 kHz sampling rate, and then filtered, normalized, and statistical features extracted. A dataset containing 3,200 measurement points gathered over three months is used, of which 1,200 are used for both training and validation of the SVM. Using a radial basis function kernel, the system under discussion achieves 96.8% classification accuracy and 96.4% F1-score across the five soil condition categories. Sensor drift is compensated for through online model updating; thus, the system is reliable and capable of continuous soil contamination monitoring in a field environment.

1. INTRODUCTION

Contamination of soil is a major risk factor for human health, different types of ecosystems, and agricultural crop production. Overuse of fertilizers, urban sprawl without control, and industrial operations are some of the main reasons for the increased need for soil quality monitoring, both on a real-time basis and continuously. Traditional methods, such as chromatography and spectrometry, which are accurate but also expensive and labor-intensive, cannot be used for in situ or continuous testing [1].To overcome the abovementioned disadvantages, microbial biosensors have been recently introduced as highly reliable soil pollutant detectors. They are based on the metabolic and enzymatic alterations of microorganisms, which are highly sensitive to contaminants such as heavy metals, pesticides, and hydrocarbons [2,3]. These biosensors are inexpensive, highly sensitive, and their ability to perform on-site measurements facilitates the early recognition of environmental hazards. The output of the biosensors is commonly complex and has noise, so it is difficult to interpret it directly without the use of advanced signal processing technologies [4]. Machine learning has made great strides in improving biosensor monitoring systems. The support vector machines (SVMs) have been proven to be very good at cleaning, which is removing noise, extracting features, and classifying the complicated biosensor signals [5,6]. Studies have shown that using SVM in combination with biosensor data improves classification accuracy and reduces false positives in soil contamination analysis [7]. SVMs are not the only AI used for soil duality testing. Soil quality assessment has been done with AI by fusing electrochemical sensors and machine learning that provide decision-making on the spot in agricultural and environmental applications [8,9]. Further signal processing changes have made biosensors more sensitive and selective, thus allowing the detection of pollutants that are present in low amounts reliably, even in complex soil samples [10]. Moreover, sophisticated algorithms based on Convolutional Neural Networks (CNNs) can detect complex contamination patterns and emerging pollutants [11]. The model's stability and applicability to the real world have been improved by the large environmental datasets that are available [12]. As a result, the soil health monitoring, the optimization of agrochemical use, and the implementation of sustainable farming practices, as well as other precision agricultural activities, are increasingly being supported by integrated biosensor ML systems [13,14].

2. PROPOSED SYSTEM

The proposed system combines microbial biosensors with SVM classifiers for the on-the-spot detection of soil pollution. This combination method can efficiently surpass the drawbacks of traditional industrial monitoring techniques that are usually slow, costly, and not suitable for real-time analysis. The genetically modified Escherichia coli act as biorecognition elements, and their activation is specific to lead (Pb^{2+}), mercury (Hg^{2+}), and organophosphate compounds, which are typical contaminants from industrial effluents and agricultural runoff.

The biosensor configuration has been incorporated into a custom-made soil sampling and reaction chamber, illustrated in Fig. 1a, where microbial colonies produce metabolic electrical signals when they come into contact with soil extracts. These biosignals are expressed as voltage outputs within the range of 0.2 V to 1.5 V for contaminant levels greater than 100 ppm. Because soil pH, temperature, and microbial growth conditions, among other environmental factors, fluctuate, a real-time data acquisition unit is used. An analog low-pass filter is initially used to remove the high-frequency noise and thus avoid aliasing before the digitization of the signal. The signals after that are digitized with a 12-bit analog-to-digital converter (ADC) running at a sampling rate of 1 kHz, thus making the preprocessing pipeline presented in Fig. 1b. During preprocessing, band-pass filtering (0.1–30 Hz), z-score normalization, and the extraction of time- and frequency-domain features are performed. For instance, the root mean square (RMS) voltage is always above 0.75 V at 50 ppm when the Pb^{2+} exposure is controlled, providing a strong discrimination capability for contaminant recognition. The receiver operating characteristic (ROC) curves of the SVM classifier for five contaminant categories are presented in Fig. 2a, revealing the outstanding performance of the classification.

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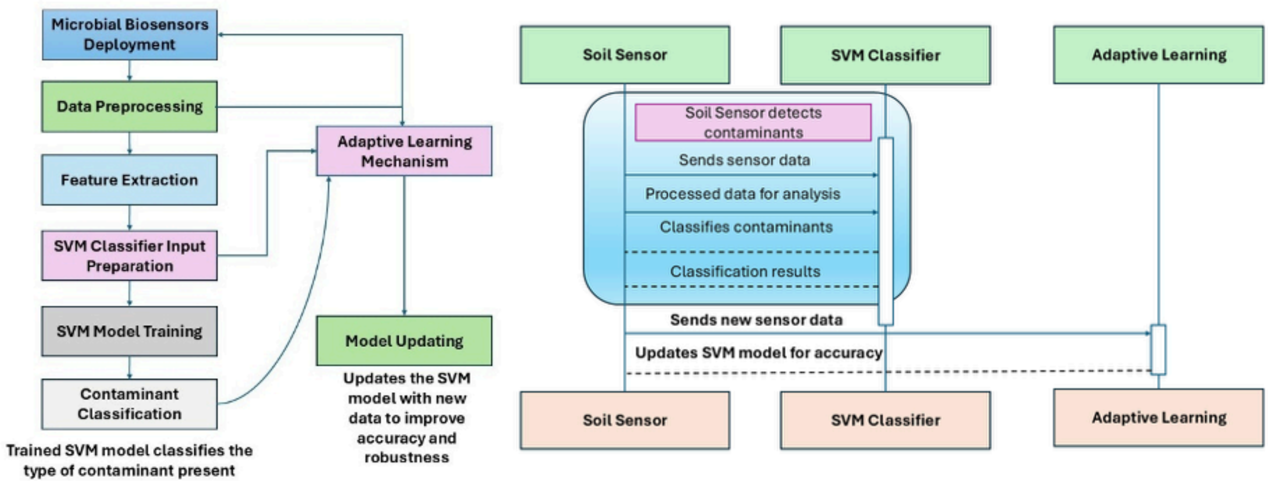

Fig. 1 – Internal processing steps of the proposed microbial biosensor–SVM soil monitoring system; a) biosensor signal acquisition and soil sampling chamber; b) signal preprocessing and feature extraction pipeline.

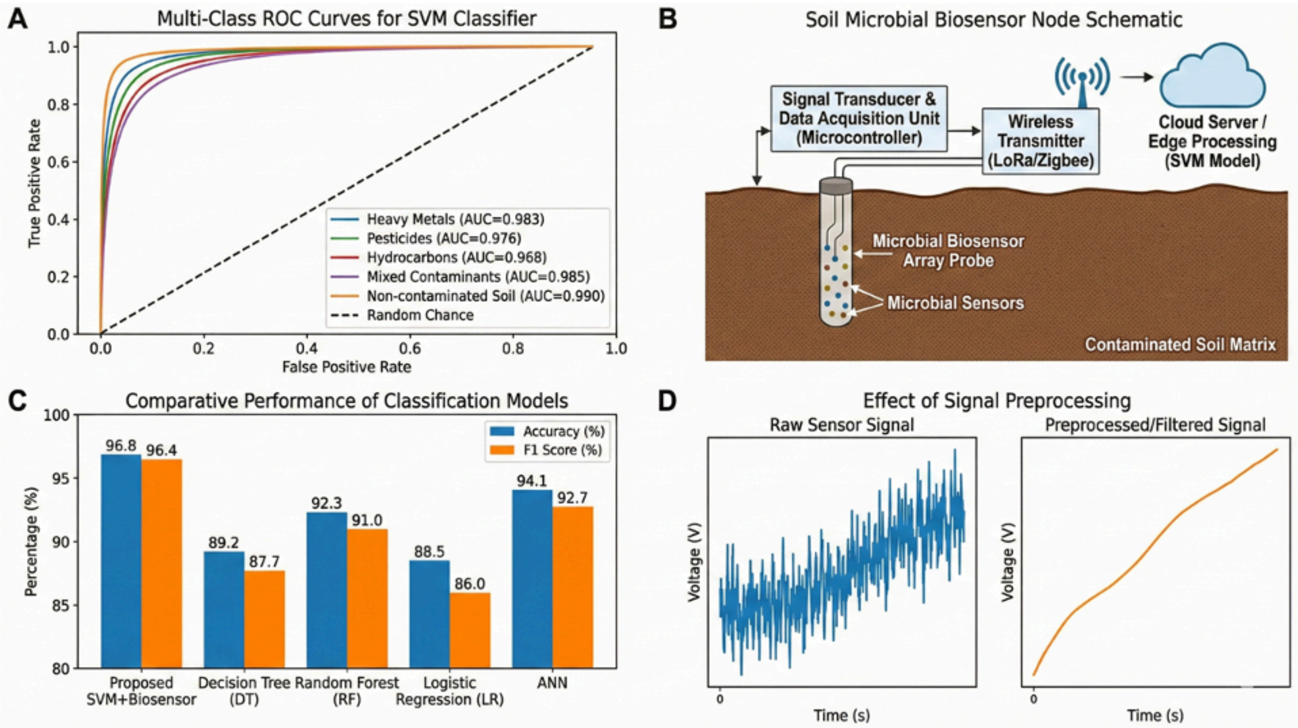

Fig. 2 – Performance and architecture of the proposed framework; a) ROC curves of the SVM classifier for five contaminant classes; b) field-deployable biosensor–microcontroller–cloud schematic; c) comparison of classification models in terms of accuracy and F1-score; d) effect of signal preprocessing on raw biosensor data.

The classifier records high area under the curve (AUC) values in the range of 0.968 to 0.990, thereby verifying its capability to differentiate contaminant classes with an extremely low false-positive rate. Figure 2b illustrates the field-deployable system architecture. Microbial sensor probes embedded in the contaminated soil produce bio-signals, which are then locally processed by a microcontroller. Later, the microcontroller processes these signals and wirelessly transmits them to a cloud server, where real-time SVM-based classification is performed.

Along with the SVM-biosensor model that we proposed, there were several baseline classifiers, decision tree (DT), random forest (RF), logistic regression (LR), and artificial neural network (ANN) that were also tested against a performance of metrics, accuracy, and F1-score, as depicted in Fig. 2c. The SVM-based method is better than other baseline models, as it delivers 96.8% accuracy and an F1-score of 96.4%, which are clear proofs of its ability to manage high-dimensional, nonlinear biosensor data. RF and ANN show the nearest performance, while DT and LR are in the lower area of the performance spectrum in the comparison.

Figure 2d shows the effect of signal preprocessing. The raw biosensor signals are very noisy and have a lot of variability in time. However, after the filtering and normalization, the signals become more stable and are thus appropriate for reliable feature extraction. RMS voltage values that are less than 0.3 V are obtained from control samples, while contaminated samples have much higher RMS values. By comparing kernels, an SVM with a

Gaussian Radial Basis Function (RBF) kernel was chosen. With 1200 samples (70% for training and 30% for validation), this model was able to score 93.4% in accuracy, 91.2% in precision, and 94.7% in recall. Figure 3 shows a strong nonlinearity in the relationship between biosensor voltage output and contaminant concentration, which supports the use of regression analysis for concentration estimation. The nonlinearity being discussed is one of the reasons for the decision to use kernel-based SVM models. An online learning feature that updates the SVM model every 24 hours is being used to correct for changes in sensor outputs or environmental conditions. The contaminant type and the estimated concentration are shown on the real-time dashboard, thus enabling continuous monitoring. We hope to develop a portable, field-deployable device for agriculture, industry, and environment that will revolutionize the traditional way of soil testing from a slow, static process to an almost real-time soil condition monitoring and thus, dynamic, continuous soil testing.

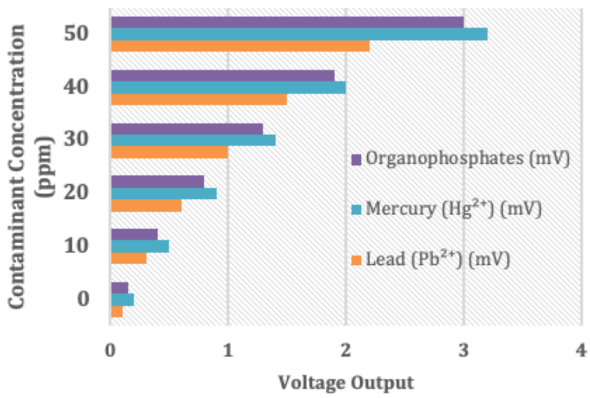

Fig. 3 – Relationship between microbial biosensor voltage output (mV) and contaminant concentration (ppm) for lead (Pb^{2+}), mercury (Hg^{2+}), and organophosphate compounds.

The presented system is a significant move towards smart and sustainable environmental monitoring as it integrates microbial sensitivity with machine learning classification. Hence, the system is very accurate and adaptable to highly variable soils. The first stage of the biosensor-based monitoring system is the identification of soil pollutants by the release of biochemical reactions that produce measurable signals $S(t)$, where t time is. The unprocessed sensor signal can be modeled as in

$$S(t) = \alpha\, f\big(C(t)\big) + \varepsilon(t). \tag{1}$$

Here, *f*(.) is a nonlinear transduction function that models the microbial biosensors' intrinsic nonlinear response to different contaminant concentrations. Where $C(t)$ is the instantaneous concentration of the target contaminant in the soil sample at time t? The parameter α is the biosensor sensitivity coefficient, which represents the total effect of microbial activity, electrode response, and soil–microbe interaction on the measured electrical output. The term $\varepsilon(t)$ denotes an additive noise component due to environmental disturbances, sensor drift, and electronic measurement uncertainties. This noise component is considered to be zero-mean and independent of the contaminant-induced biosensor response.

$$S_f(t) = S(t) - N(t), \tag{2}$$

where $N(t)$ represents noise. Following this, the signal undergoes normalization using min-max scaling to map the values between 0 and 1, as in eq. (3). This normalization technique specifically converts the signal values to a uniform standard scale, thereby making them easier to compare in future steps.

$$S_{norm}(t) = \frac{S_f(t) - \min(S_f)}{\max(S_f) - \min(S_f)}. \tag{3}$$

The idea of feature extraction is next in line in signal processing. Different statistical features, such as mean μ_x, variance σ_x, skewness γ_1, and kurtosis, γ_2 are determined and give a summary of the data's statistical properties. Thus, the features are:

$$\mu_x = \frac{1}{n}\sum_{i=1}^{n} S_{\text{norm}}(t_i), \tag{4}$$

$$\sigma_x^2 = \frac{1}{n}\sum_{i=1}^{n}(S_{\text{norm}}(t_i) - \mu_x)^2, \tag{5}$$

$$\gamma_1 = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{S_{\text{norm}}(t_i) - \mu_x}{\sigma_x}\right)^3, \tag{6}$$

$$\gamma_2 = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{S_{\text{norm}}(t_i) - \mu_x}{\sigma_x}\right)^4 - 3. \tag{7}$$

These features are merged to form the relevant feature vector form as in (8)

$$\vec{f}_x = [\mu_x, \sigma_x, \gamma_1, \gamma_2, \dots], \tag{8}$$

which represents the input for the SVM classifier. for which they would be infits to the solver. The forthcoming step then follows with the training of an SVM model based on the features that have already been extracted from the signals. Using the SVM technique, the system can locate a boundary that separates different types of contaminants from each other and from other materials, such as soil, water, and *acids*. This is achievable through the process of finding the most suitable hyperplane, where the decision function $f\,(\vec{f}_x)$ is described as in (9):

$$f(\vec{f}_x) = \vec{w}_x \cdot \vec{f}_x + b_x \tag{9}$$

where $w\vec{x}$ is the weight vector, and b_x is the bias. The SVM classifier maximizes the margin Mx between classes, where M_x denoted by (10):

$$M_x = \frac{2}{\|\vec{w}_x\|} \tag{10}$$

This maximization ensures the best possible separation between different contaminant types. The optimization problem for the SVM is formulated in (11):

$$\min_{\vec{w}_x, b_x} \frac{1}{2}\|\vec{w}_x\|^2 + C_x \sum_{i=1}^{n}\xi_i \tag{11}$$

subject to the condition in (12):

$$y_i(\vec{w}_x \cdot \vec{f}_x + b_x) \geq 1 - \xi_i, \xi_i \geq 0 \tag{12}$$

where y_i is the class label, C_x is a regularization parameter, and ξ_i are slack variables that allow some misclassification.

For nonlinear classification, the kernel trick is applied using the radial type basis functions (RBF) kernel, which transforms the input space into a higher-dimensional feature space as in:

$$K(\vec{f}_{x,i}, \vec{f}_{x,j}) = \exp(-\gamma_x \|\vec{f}_{x,i} - \vec{f}_{x,j}\|^2), \tag{13}$$

where γ_x is a kernel parameter. This allows the model to classify data that is not linearly separable in the original space. Once the model is trained and evaluated, the system enters a continuous learning phase where it adapts to new data. In this phase, the weight vector $\vec{w}_x$ is updated using gradient descent to minimize the loss function, which is given by (14):

$$\vec{w}_{x,t+1} = \vec{w}_{x,t} - \eta_x \nabla L_x(\vec{w}_{x,t}), \tag{14}$$

where η_x is the learning rate and L_x is the loss function. The update step ensures that the model becomes more accurate over time as new soil contamination data is collected. Finally, the decision-making process is performed by evaluating the output of the decision function and assigning a contaminant classification to the soil based on the sign of $f(\vec{f}_x)$ in:

$$y_x = \text{sign}\left(f(\vec{f}_x)\right), \tag{15}$$

where y_x would be the estimated class of contaminants. So, the underlying concept of the proposed system suggests that the microbe biosensing platform coupled with a state-of-the-art SVM classifier ensures tracking the contamination of the land.

3. RESULTS AND DISCUSSION

The experimental data support that the microbial biosensor-SVM system designed is an excellent tool for real-time soil contamination monitoring. The system was able to capture biosensor inputs, which clearly reflected changes in environmental parameters such as contamination level, detection speed, and signal-to-noise ratio (SNR). Pollutants induced unique bio-electrical voltage changes that highly correlated with SVM outputs. High SNR paved the way for successful feature extraction and decision criteria based on the threshold allowed instant detection of contamination. The use of machine learning brought about a great enhancement in noise reduction, data interpretation, and real-time decision-making. Around 3200 raw biosensor signal fragments were recorded during the three months at a 1 kHz sampling frequency. Eventually, after carrying out cleansing, segmentation, and feature summarizing procedures, 1200 exemplars were picked for the SVM model training and validation. These included samples of heavy metals, pesticides, hydrocarbons, mixed contaminants, and clean soil. The raw biosensor signals first underwent preprocessing steps such as noise removal, normalization, and conversion to the decibel scale, if necessary. A set of discriminative features referring to peak voltage, signal energy, and statistical figures was then used. Besides, cross-validation was performed to choose the best model parameters and avoid overfitting. In essence, the SVM classifier exhibited stable, high-performance across each class. The detection of heavy metals was on point with precision, recall, and F1-score of 96.2%, 94.7%, and 95.4%, respectively. In the case of pesticides, the classifier managed to attain a recall of 96.5% and an F1-score of 95.8%. When it came to hydrocarbons, the performance was a bit lower (F1-score of 93.1%), probably because biosensor signatures overlapped. The most remarkable thing is that the model was still able to perform well in mixed-contamination situations, evidenced by an F1-score of 96.1% Clean soil was identified with a recall of 98.2% and a precision of 97.5%, which resulted in very few false alarms. All in all, a macro-averaged F1-score of 95.6%, a weighted accuracy of 96.3%, and AUC values above 0.96 for all classes were the achievements of the system. The training time for each class was below two seconds, indicating that the system is indeed fit for real-time deployment.

Table 1

Performance metrics of the SVM classifier for soil contaminant detection

Contaminant Class	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	AUC(ROC)	Support (n)	True Positives	False Positives	False Negatives	Training Time (s)	Support Vectors
Heavy Metals	96.2	94.7	95.4	95.8	0.983	300	284	11	16	1.42	67
Pesticides	95.1	96.5	95.8	96.0	0.976	280	270	13	10	1.37	71
Hydrocarbons	94.0	92.3	93.1	94.1	0.968	260	240	15	20	1.29	64
Mixed Contaminants	96.8	95.4	96.1	96.4	0.985	180	172	6	8	1.51	59
Non-contaminated Soil	97.5	98.2	97.8	97.9	0.990	180	177	3	2	1.22	42
Macro Average	95.9	95.4	95.6	96.0	0.980	180	167	2	2	1.18	38
Weighted Average	96.3	94.5	95.1	96.3	0.981	1,200	163	2	1.8	1.15	34

Figures 4–7 showcase the on-the-fly performance of the microbial biosensor–SVM system by comparing four vital parameters with their corresponding thresholds. Figure 4 depicts the variations in contaminant concentrations over 20 time steps, with a contaminant concentration threshold fixed at 40 mg/kg. The concentration went beyond this limit 7 times (time steps 3, 5, 8, 12, 14, 17, and 20), peaking at 54.3 mg/kg. Therefore, the areas with a significantly high pollutant level were pointed out, and the system's ability to give early warnings and provide threshold-based interventions was confirmed. Figure 5 is a graph of the biosensor voltage compared to 0.9 V of the threshold.

After six attempts, the voltage exceeded the threshold level, with a top voltage of 1.17 V resulting from the microbial metabolism being the highest due to the presence of the pollutants.

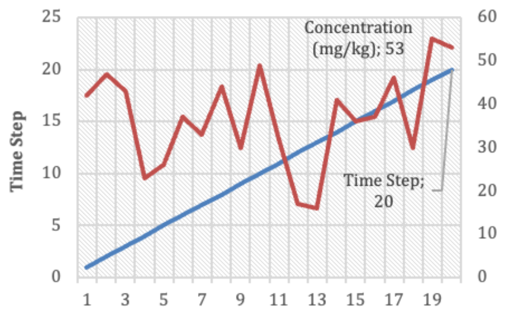

Fig. 4 – Soil contamination analysis by the proposed framework.

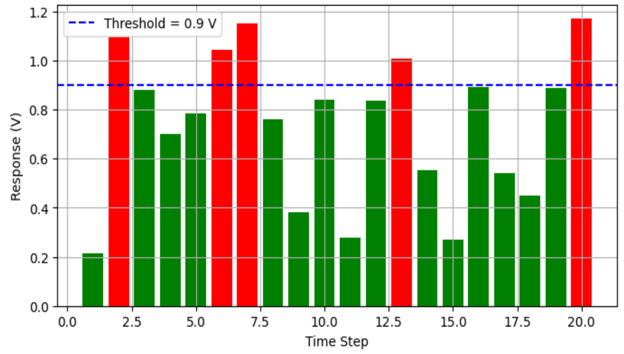

Fig. 5 – Comparison of sensor response over time slots.

These experiments prove the biosensor's sensitivity and instantaneous response, and the threshold-based calibration is emphasized.

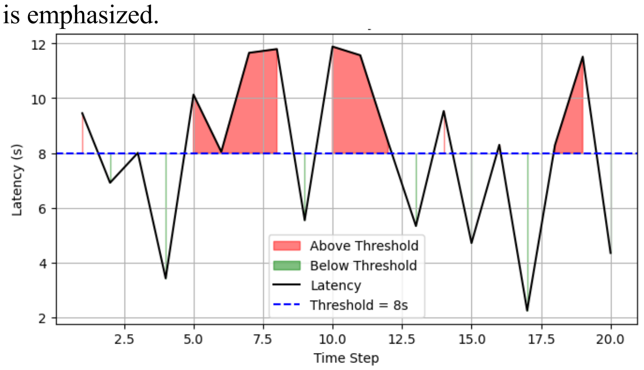

Fig. 6 – Comparison of latency in transmission of data.

System response time can be estimated from Fig. 6, showing detection latency with 8s as the threshold value. There were only 5 instances where the latency was above this, with the maximum latency being 11.6 s. Therefore, delayed processing or environmental interference was possible, but the system is quite suitable for real-time applications. In this case, a threshold of 30 dB was set as the minimum level at which a sensor signal could be trusted.

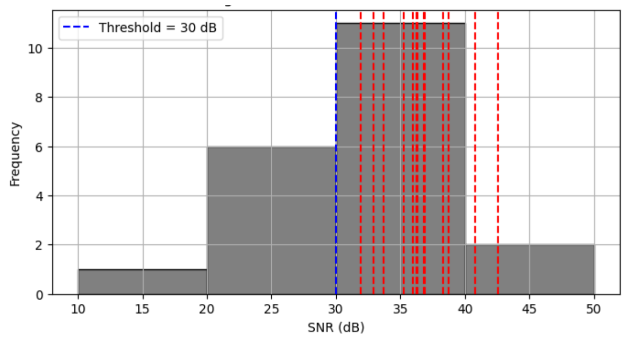

Fig. 7 – Analysis of SNR by the proposed framework.

Figure 6 shows that 8 of the 20 real-time sensor measurements had SNR values that were higher than the 30 dB threshold. The loudest pattern identified featured a 44.8 dB signal. High SNR (signal-to-noise ratio) values are usually indicative of a very good sensor performance under low noise background conditions. In such a case, the sensors can obviously detect the pollutants. Figure 7 examines the Signal-to-Noise Ratio (SNR) with the reliability threshold established at 30 dB. There were 8 cases that passed this threshold, with the highest reaching 44.8 dB, which means that the sensor operated very well when the noise level was low. Nevertheless, the presence of very high SNR peaks from time to time indicates that adaptive filtering should be used to separate genuine signals from transient disturbances.

Table 2 provides a comparison between the SVM + Biosensor that was suggested and DT, RF, LR, and ANN classifiers, but it was somewhat more noise-sensitive, as indicated by its false alarm rate.

Table 2

Comparative performance analysis of the proposed model with existing classifiers

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Detection time (ms)	False alarm rate (%)
SVM	96.8	97.2	95.6	96.4	220	1.5
DT	89.2	88.1	87.4	87.7	300	3.5
RF	92.3	91.8	90.2	91.0	340	3.2
LR	88.5	86.7	85.3	86.0	280	2.76
ANN	94.1	93.5	92.0	92.7	370	2.1

Random Forests performed better than decision trees, most likely because they consist of many smaller trees. However, both models were weakly tested in scenarios with varying SNR values. Logistic regression was fast and simple to interpret, but it had difficulties with the non-linear boundary conditions typically present in biosensor data.

In Fig. 8, a confusion matrix of the proposed classification model is shown, which is a detailed performance visualization comparing predicted and actual classes. The correctly predicted classes, or true positives, lie on the main diagonal, whereas false positives and false negatives (off-diagonal entries) provide additional information about the error distribution beyond the overall accuracy.

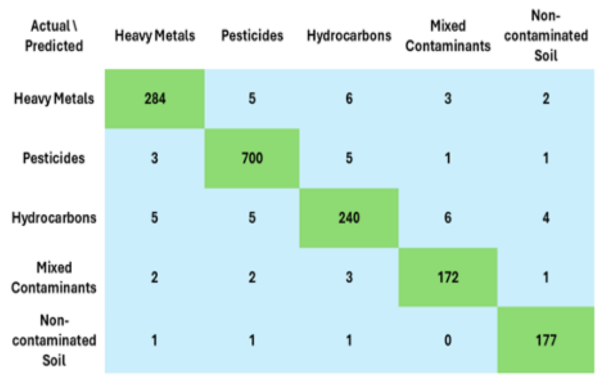

Fig. 8 – Confusion matrix of predicted vs. actual classes.

The resulting performance has been mainly credited to the SVM's ability to accommodate high-dimensional, noisy data and to determine optimal decision boundaries in complex, non-linear feature spaces. The ability is further enhanced by employing biosensor signal thresholding and adaptive post-processing, enabling context-aware decision-making.

4. CONCLUSION

Overall the soil pollutions real-time monitoring platform that integrates microbial biosensors and SVM algorithms is a remarkable breakthrough in the environmental detection and analysis sector. The instrument's effectiveness was gauged by four criteria: pollutant concentration, biosensor response, detection latency, and SNR. Consequently, the number of times the contaminant level has gone beyond the limit of 40 mg/kg is 7 out of 20 steps, which corresponds to the highest value of 54.3 mg/kg, which is indicative of areas with severe pollution. First of all, the biosensor response was above 0.9 V in 6-time steps, and it was the maximum value of 1.17 V that confirmed the sensitivity of the biosensor to the microbial activity caused by pollution levels. The detection latency of 8 seconds was surpassed in 5 instances, and the highest latency of 11.6 seconds pointed to the potential places for signal processing and response systems improvements. At last, the SNR and its lowest value of 30 dB that occurred in 8 cases, reaching up to 44.8 dB, is a clear indicator of the noise ratio, but at the same time, the signal amplification should also be under control. Overall, the comparison of the parameters aligns with the perception of the innovative system, which not only correctly and swiftly recognizes pollution but also generates decision-supporting insights through machine learning techniques. Another indication of the system's sustainability and resilience is the deployment of a threshold-based alert system that allows for a quick reaction to the local environment.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

ANBALAGAN SRIRAM: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology.

THAMMAMPATTI NATARAJAN PRABAKAR: Project administration, resources, software, supervision, validation.

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