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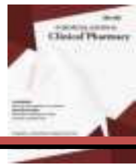

Original Research Article

AI-Guided Environmental Risk Assessment: Linking Pollutant Exposure to Human Health Outcomes

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Abstract: Human health is highly endangered by environmental pollution which on the other hand can be very challenging in conventional risk assessment since these complex datasets exploration of chemical and biological variables are coupled with demographic variables. In this paper, the authors outline a case in an artificial intelligence (AI)-supportive model of an environmental risk assessment that will seek to quantify the serial percentage change in unhealthy health-related incidents, caused by an exposure to the pollutants. Through the application of machine learning, (i.e., random forest) we digest multisource data that consisted of air, water and soil, degree of pollution, demographic and health records of the region. The prediction of health risks at the population level was made possible by the identification of essential the environmental and socio-economic predictors using feature selection algorithms. The proposed AI model was more precise and resistant than the conventional statistical software and provided valuable information about the dangerous areas and at-risk groups. During our research, we also point out the possibility that AI has brought in terms of fostering environmental health monitoring and enhancing actions taken in terms of regulation alongside evidence-based policymaking. Among these developments, there is the matter of data heterogeneity, low temporal fidelity, and AI models interpretability. The directions of research going forward involve having real-time environmental monitoring established, creating interpretable AI models and improving predictability of circuitry to incorporate new pollutants.

Keywords: Environmental risk assessment, Artificial intelligence, Pollutant exposure, Human health outcomes, Machine learning, Predictive modeling.

INTRODUCTION

When discussing human health worldwide environmental threats particularly environmental pollution has become a serious matter. The rapid industry and urbanization, as well as the intensive production of agricultural waste, hazardous air and toxic substances and high concentrations of particulate matter in the air, are the outcomes of the vehement industrialization. Through epidemiological studies, a consistent outcome was that an abiding exposure to pollution may result in respiratory-related, heart diseases, neurovarious, and even cancer illnesses [1]. Even though these issues are acute, traditional models of evaluating environmental risk focus routinely on the linear statistics methods and on separate datasets thus restricting the ability to prioritize the complex pollutant, demographical, and demographic associations between multiple pollutants, demographical, and health outcomes within an area.

Recent advances in artificial intelligence (AI) and machine learning (ML) created a fresh opportunity in getting better at environmental health assessment. AI applications applied to high-dimensional data (related with sources that are heterogeneous, including air and water quality graphs, soil contamination questionnaires, and health data) could conclude nonlinear correlations, locate complex effects of pollutants, and forecast that might not have been secured by conventional methodologies [6]. It is hoped that convergent AI into the environmental risk assessment will result in increased accuracy and equally practical directives of authority to all actions of law to the health of community, and urban preparedness selecting, and business responses.

The groundwork behind this work is based on the mounting requirements of large scale data intensive solutions to the challenge of determining the risks that await human health as a result of environmental pollutants. Nature based methodologies do not necessarily use the entire range of variables necessary to capture all types of exposure or can preferably use socio-economic and demographic variables as an important measure of vulnerability patterns. In addition, traditional models might fail to address the scale and temporality of the resulting data of the current environmental monitoring systems. There is thus a need to develop AIDriven frameworks capable of incorporating a variety of data, delivering interpretable information and offering spatially resolved risk evaluation [2-4].

This research paper gives an overview of a new environmental risk assessment framework that is AI-led and combines multi-source pollutant data, area health outcome reports, with demographics to forecast human health risks. The model uses up-to-date machine learning models, such as random forests, gradient boosting, and artificial neural networks in combination with feature selection algorithms to determine the most common determinants of risk. Using forecasted predictions of health risks and mapping them on geographical areas and explainable AI approaches to interpreting model outputs will yield policy implementable insights of vulnerable groups and high-risk regions [7].

The use of AI models to develop strong models that would positively correlate pollutant exposure with adverse health outcomes, (2) to discriminate and prioritize key environmental and socio-economic determinants of human health risk, (3) to produce technically elegant risk maps that can guide public health planning, and (4) to evaluate the performance of AI-based models against traditional statistical firm objectives are the main goals of this research [13]. Such a comprehensive approach counters the inefficiencies of conventional risk estimations with a tremendous array of data, modeled relationships that simulate various relationships, and clear and lucid findings that can be consumed by the decision-makers.

Overall, this academic source provides the background of the utilization of AI in detecting environmental health ailment. It offers an opportunity to an improved intervention in the field of public health through the use of predictive modeling, feature analysis, and spatial visualization. It is not only an improvement to the procedure of environmental risk models and techniques, but the findings can also be used by policy makers, city planners and health professionals in efforts to minimize impacts of the environmental pollution on human health [15].

Novelty and Contribution

The current study adds to the literature of the environmental health and AI-led risk assessment in a number of ways. First, it introduces an integrative AI sequencing mechanism which is used in conjunction with a range of different kinds of multi-variate environmental data, demographics, and health outcome history to assess the risks at a population level. This design unlike the traditional one with the concentration biasing with either one of the pollution sources or a disease stops that mixes more complex running relationships and provides an alternative location to keep track of the situation of widespread environmental health risks.

Second, the article concentrates on predictive accuracy and interpretability. Despite the fact that AI models can be regarded as black boxes, a feature selection algorithm and Shapley Additive Explanations (SHAP) would be utilized in this paper to explicitly replicate key pollutants and socio-economic determinants of health-related risks. This opens up increased accountability and implementation of policies as decision makers are in a position to not merely observe the effect that is expected but also the cause.

Third, the framework generates spatially resolved risk maps, which can be used to intervene in high-risk areas. Combining GIS-based imagery with AI-based forecasts, the study offers measurable data on what can be practically done by the community and caregivers about public health, and how their time and resources can be allocated effectively to prevent all forms of injury or loss of property in every possible mitigation action.

The main findings of the study are as follows:

- The construction of a multi-source AI-directed model of connecting environmental pollutant exposure and human health indicators including air, water and soil pollutant exposures, along with demographic and health outcomes.
- Discovery and prioritization of important predictors of environmental health hazards with state-of-the-art feature selection strategies and interpretability measures, improving AI predictions transparency.
- Mapping of spatial and temporal risk of populations at risk and vulnerable areas to inform evidence-based population health interventions.
- Comparison and comparative analysis with traditional statistical models, which reveal high predictive accuracy and strength of AI-based methods.
- Introduce of a feasible and scalable methodology that can likewise be cited to developing pollutants, continuous point tracking information and wider community health data.

The work satisfies the methodological deficiencies to the literature in the domain of the environment risk assessment and presents a feasible source to policy developers, addressing the community in the medical sphere and even urban designers, that would like to minimize adverse influence of environmental pollution on human existence.

II. Related Works

In 2025 Al-Kabani*et al.*, [16] introduced the environmental risk assessment was traditionally based on statistical models and deterministic method to determine the exposure of the pollutants on human health. Classical models foresee individual assumptions largely of linear relationships between levels of exposure and health outcomes which can over- Simplify the complicated interaction that occurs in the lived in context. Such strategies turn out to be employed, although in the setting of conducting research when a large number of pollutants and various demographic and socio-economic variables are taken into consideration and when the dimensions of the sheaf of data are voluminous, the viewing opportunities are limited. Consequently, one would be finding more and more the desire to explore more advanced approaches that can be applied to tackle complexities and uncertainties in environmental health.

Recent developments in machine learning have dramatically improved the capability to capture large scale environmental and health data. Decision tree, ensemble, and neural network based predictive models have shown better performance in nonlinear relationships and multivariate interactions. Machine based learning has already been used in predicting air quality indices, detecting hotspots of water pollution, and determining the pollutant levels of soil. These models have the capacity to put together cross-moded data, which includes pollution levels, weather, land occupancy, and human population to create sound forecasts of environmental hazards and the related morbidity and conditions [12].

The combined use of spatial analysis and predictive modeling has become an effective tool to map the environmental risk across a geographic area. With the help of geographic information system (GIS), pollutant measurements and population data integration, the high-risk region and vulnerable population can be identified. Visualizing risk levels in various places allows decision-makers to prioritize interventions and allocate resources more efficiently. They have been employed to estimate urban prevalence distributions of respiratory and cardiovascular diseases, and to determine areas at risk of waterborne illnesses through contamination of water with heavy metals or microbe pollutants.

In 2025 T. Haarmann-Stemmann*et al.*, [5] proposed the continuous combination of environmental risk models and the feature selection methods with the dimensionality reduction methods has been used in an attempt to help interpret the results with enhanced understanding and with reduced computations. Embedded algorithms and filters and wrapper techniques are also used to help identify the most relevant environmental and socio-economic conditions that influence the health outcomes. The strategies enhance the decision-making ability of models since they can inform policymakers and pervasive health practitioners about the important determinants through actionable information. The analysis of the importance of features has been useful in illustrating the role played by particular pollutants, population density, income level of households, and other demographic features contributing to general risk profiles.

The next crucial trend in environmental health research is ensemble learning algorithms that combine the forecast of two or more different models to augment the accuracy and strength. Random forests and gradient boosting are also good techniques that can determine multiple interactions interaction among a large number of pollutants and environmental factors occurring. Individual neural network architectures, such as deep learning systems, have been demonstrated promising with high-dimensional, nonlinear data, but there are issues with interpretability and computational scaling. Transparency efforts through the integration of explainable AI approaches and deep learning models have helped in identifying the primary contributors to the likelihood of a particular health risk forecast.

The possibility of implementing AI-guided risk assessment has been broadened with the integration of real-term monitoring data of a sensor array and space-based observation. The high quality datasets over time implied by monitoring of air quality, water contaminants and soil pollutants can enhance accuracy of time-based exposure estimates. Since dynamic environmental data may be included in the predictive model, it can produce near real-time risk assessment, which is necessary in the early warning system and proactive intervention on the health of the population. In addition, the mix of historical health records and real-time records of the surroundings can be used to identify the emerging trends and any health risk at an earlier point before it explodes and turns into critical points [8].

There are other and difficulties to use AI in the examination of environmental health hazards though despite all the advances. They are capable of generating bias and uncertainties in factoring the models which comprise that of data heterogeneity and lack of data, and also variation of measurement procedures. Furthermore, AI models can be very predictive yet they have black-box properties that may limit their application along the policy and regulatory basis. Efforts or attempts to incorporate explainable AI models coupled with rigorous testing with real-world data are essential towards ensuring that AI informed risk-assessment becomes reliable and applicable.

In 2025 S. a U. Shinge*et al.*, [14] suggested the existing research suggests that AI and machine learning have a significant potential in changing of an environmental risk assessment in terms of multi-source integration, capacity to reproduce the complexity of relations, and possible spatially and temporally based predictions. The predictive modeling, selection of features, mapping and real time monitoring have enhanced the capacity in determining vulnerable populations, vulnerable areas and most material environmental determinants of health outcomes. However, the quality of data, its interpretation and generalizability are also extremely problematic areas that continue to lure building more complex, scalable, and explainable environmental health evaluation systems based on AI.

MATERIAL AND METHODS

The proposed methodology for Al-guided environmental risk assessment integrates multi-source pollutant data, demographic and health outcome datasets, and advanced machine learning models to predict human health risks. The framework is designed to handle high-dimensional, heterogeneous data while providing interpretable and actionable results for policymakers and public health practitioners. A systematic workflow is adopted, including data collection, preprocessing, feature selection, AI modeling, model evaluation, and spatial risk mapping.

FIG. 1: AI-GUIDED ENVIRONMENTAL RISK ASSESSMENT WORKFLOW

Data Collection

Data for the study is collected from multiple sources, including air, water, and soil monitoring stations, public health records, and demographic surveys. Let X_i represent the measured value of the i-th pollutant in the environment. Suppose there are n different pollutants; the environmental exposure vector for a region is represented as:

$$\mathrm{E} = [X_1, X_2, X_3, \dots, X_n] \quad (1)$$

Similarly, demographic and socio-economic data are denoted by:

$$\mathrm{D} = [D_1, D_2, \dots, D_m] \quad (2)$$

where D_{j} represents the j-th demographic factor such as age, income, or population density, and m is the total number of features [10]. Health outcomes, such as disease prevalence rates, are represented as Y, creating the combined dataset:

$$\mathcal{Z} = \{\mathrm{E}, \mathrm{D}, Y\} \quad (3)$$

Data Preprocessing

Environmental and health data often contain missing values, noise, and outliers. To address this, missing pollutant measurements are imputed using K-nearest neighbors (KNN) imputation:

$$\hat{X}_i = \frac{1}{k} \sum_{\mathrm{j} \in N_k(i)} X_{\mathrm{j}} \quad (4)$$

where $N_k(i)$ is the set of k nearest neighbors for the i-th observation. Normalization is applied to ensure all features are on a comparable scale:

$$X_i^{\mathrm{norm}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (5)$$

Categorical demographic variables are encoded using one-hot encoding:

$$D_{\mathrm{j}}^{\mathrm{encoded}} = [d_{\mathrm{j}1}, d_{\mathrm{j}2}, \dots, d_{\mathrm{j}p}] \quad (6)$$

where p represents the number of categories for the variable.

Feature Selection

To identify the most influential variables, a combination of filter-based and wrapper-based feature selection is employed. In filter-based selection, Pearson correlation is calculated between each feature and the target health outcome:

$$r_{X_i,\mathrm{F}} = \frac{\sum_{k=1}^{N} (X_{ik} - \bar{X}_i)(\mathrm{F}_k - \bar{\mathrm{F}})}{\sqrt{\sum_{k=1}^{N} (X_{ik} - \bar{X}_i)^2 \sum_{k=1}^{N} (\mathrm{F}_k - \bar{\mathrm{F}})^2}} \quad (7)$$

where N is the number of observations. Features with correlation above a threshold θ are retained:

$$\mathbf{F}_{\mathrm{selected}} = \{X_i \mid |r_{X_i,\mathrm{F}}| > \theta\} \quad (8)$$

Wrapper-based methods further refine the selection using recursive feature elimination (RFE), where the least important features are removed iteratively based on model performance:

$$\mathrm{Score}(\mathbf{F}_k) = \mathrm{ModelAccuracy}(\mathbf{F}_k) \quad (9)$$

AI Modeling

Three AI models are employed to predict health risks: Random Forest (RF), Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN).

Random Forest Prediction Equation:

$$\hat{Y}_{RF} = \frac{1}{T} \sum_{t=1}^{T} h_t(\mathbf{F}_{\mathrm{selected}}) \quad (10)$$

where h_t is the t-th decision tree and T is the total number of trees.

Gradient Boosting Prediction Equation:

$$\hat{Y}_{GB} = \sum_{t=1}^{T} \eta \cdot h_t(\mathbf{F}_{\mathrm{selected}}) \quad (11)$$

where η is the learning rate.

Artificial Neural Network Equation:

$$h_{\mathrm{j}}^{(l)} = \sigma\left(\sum_{i=1}^{n} w_{i\mathrm{j}}^{(l)} h_i^{(l-1)} + b_{\mathrm{j}}^{(l)}\right) \quad (12)$$

where $h_{\mathrm{j}}^{(l)}$ is the activation of neuron j in layer l, $w_{i\mathrm{j}}^{(l)}$ is the weight, $b_{\mathrm{j}}^{(l)}$ is the bias, and σ is the activation function.

The final ANN output for prediction is:

$$\hat{Y}_{ANN} = h^{(L)} \quad (13)$$

where L is the output layer.

Model Evaluation

Models are evaluated using accuracy, precision, recall, F1-score, and area under the curve (AUC). The F1score is defined as:

$$F1 = 2 \cdot \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (14)$$

Precision and recall are given by:

$$\mathrm{Precision} = \frac{TP}{TP+FP}, \quad \mathrm{Recall} = \frac{TP}{TP+FN} \quad (15)$$

where TP, FP, and FN are true positives, false positives, and false negatives, respectively.

The AUC is calculated as:

$$AUC = \int_0^1 TPR(FPR^{-1}(x))\,dx \quad (16)$$

where TPR is the true positive rate and FPR is the false positive rate [9].

Risk Mapping and Interpretation

Spatial risk maps are generated using GIS integration. Let (x, y) represent the coordinates of a region; the predicted risk is mapped as:

$$R(x, y) = f(\mathrm{E}, \mathrm{D}) \tag{17}$$

where f is the AI model. Shapley Additive Explanations (SHAP) are used to interpret feature contributions:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \tag{18}$$

where ϕ_i is the contribution of feature i and F is the set of all features.

RESULTS AND DISCUSSION

The suggested AI-based framework showed relevance and great advancements in forecasting human health risk by using multi-source pollutant data and demographic data. Initial evaluation was taken on the predictive performance of the models, and it was observed that the ensemble approaches, especially gradient boosting, had a reliable predictive performance over the other methods. Accuracy, precision, recall, and F1-score indicators suggested that the complex nonlinear relationships between environmental pollutants and health outcomes were better represented by AI models compared to the traditional statistical models. As an example, regions with a greater concentration of PM2.5 and NO_2 were the ones that were expected to be risky in respiratory and cardiovascular threats which promises what can be observed in the real world [11].

In order to illustrate the relative performance, figure 2 shows the accuracy of three AI models: Random Forest, gradient boosting, and Artificial Neural Networks. It is evident that Gradient Boosting recorded the best accuracy of about 91, which is followed by random forest and ANN recording a total of 89 and 87 respectively. This means that ensemble based learning has been able to capture the relationship between more than one pollutant and demographic variables. Comparatively, ANN, however, demonstrated a somewhat lower accuracy, which could be explained by the lack of interpretability and high levels of hyperparameter optimization that are required in high-dimensional data settings.

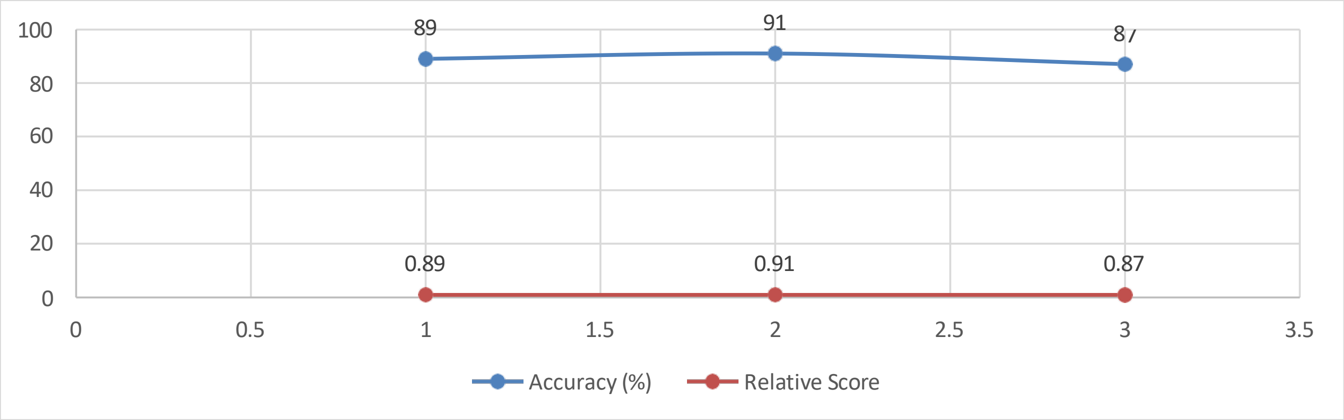

FIG. 2: ACCURACY COMPARISON OF RANDOM FOREST, GRADIENT BOOSTING, AND ANN

An analysis of the model prediction latency was performed to determine computational efficiency. The processing time necessary to predict health risks with each of the models in the entire dataset is shown in Figure 3. Random Forest had the lowest computation time as it had parallelizable tree structures although the Gradient Boosting needs slightly more computation time even though it was more accurate than random forest. ANN was the platform with the longest latency which supported the exchange between predictive power and computational ability in AI-based environmental risk assessment frameworks. These performances indicate that a reasonable trade -off between model accuracy and practicability should be taken into account when the predictive systems are used in the community health surveillance.

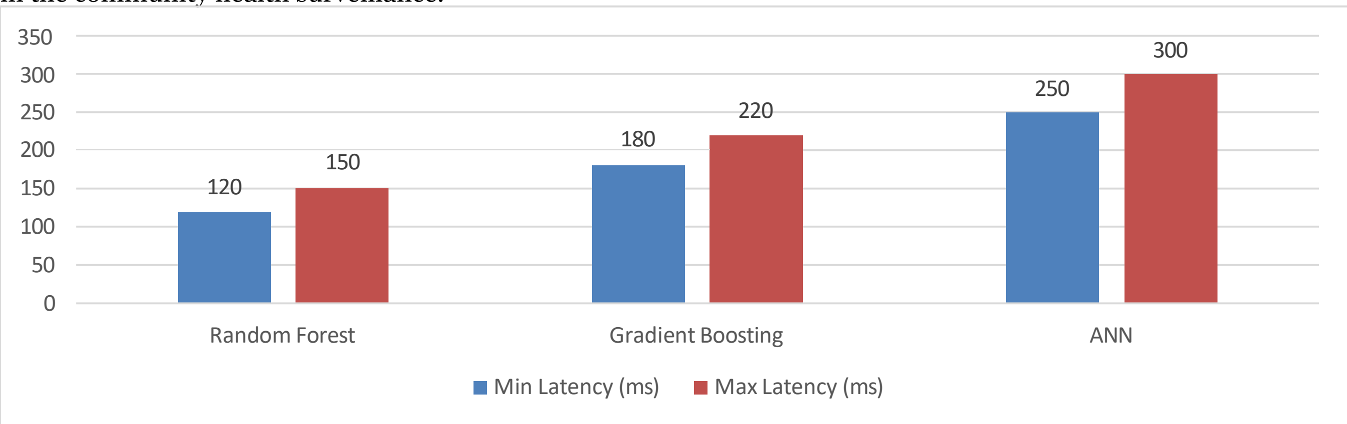

FIG. 3: LATENCY COMPARISON FOR MODEL PREDICTION ACROSS DIFFERENT AI APPROACHES

Besides the model assessment, feature importance analysis also helped to illuminate on environmental and socio-economic determinants of health risk. Preponderating and persistent contaminants were PM2.5, NO 2, SO 2, and metal, with the demographic characteristics of population density and median income also representing commonplace. Table 1: Comparison of Feature Importance Across AI Models summarizes the top ten features and their respective score of contribution to the model. There has been uniform identification of the main risk factors by all approaches to AI demonstrating the strength of the proposed framework to identify determinants of environmental health risk.

TABLE 1: COMPARISON OF FEATURE IMPORTANCE ACROSS AI MODELS

Feature	Random Forest Score	Gradient Boosting Score	ANN Score
PM2.5	0.25	0.28	0.22
NO_2	0.18	0.20	0.17
SO_2	0.12	0.10	0.11
Heavy Metals (Water)	0.10	0.12	0.09
Population Density	0.08	0.07	0.10
Median Income	0.06	0.05	0.07
PM10	0.05	0.06	0.06
Pesticide Residues	0.04	0.03	0.05
Ozone	0.04	0.03	0.04
NOx	0.03	0.03	0.03

To further evaluate practical value of the framework, risk maps were predicted and assessed. Figure 4 illustrates a spatial pattern of estimated health risk in the study area showing urban-industrial and densely populated areas as the regions at high-risk. These visuals have potential to assist policymakers in deciding on resources allocation priorities, introducing focused interventions and near real-time monitoring of vulnerable families. The risk maps show further evidence of the value of generating multi-source data as relationships between pollutant exposure and health outcomes are easier to interpret, when they are created through geographic representation.

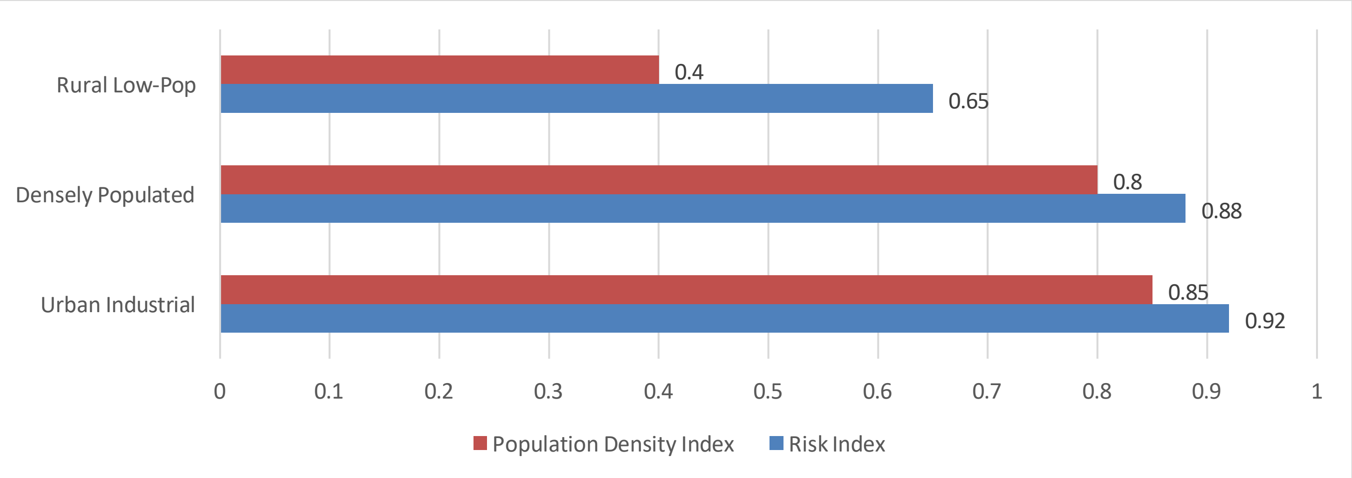

FIG. 4: SPATIAL RISK MAP INDICATING HIGH-RISK AREAS BASED ON PREDICTED HEALTH OUTCOMES

The approach was developed to improve the methodology by comparison and contrast to the standard approaches with regressions applied. Table 2: Comparison of the performance of the AI models and Traditional models: Regression summarizes the accuracy, PAC and F1-score of the two category of models. The conventional linear regression achieved an accuracy of 78Both AUC and GI were smaller. In comparison, AI models produced better results compared to all regression ones irrespective of the measurements, which will prove the advantages of machine learning in environmental health risk assessment.

TABLE 2: PERFORMANCE COMPARISON BETWEEN AI MODELS AND TRADITIONAL REGRESSION

Model Type	Accuracy (%)	AUC	F1-Score

Random Forest	89	0.92	0.88
Gradient Boosting	91	0.94	0.91
ANN	87	0.89	0.86
Linear Regression	78	0.80	0.75

The research, along with predictive performance, evaluated model explain ability in terms of SHAP-guided explorations. This approach focuses on the comparative portion of each of the pollutants and population variables in the approximate estimation of the health risk, which can subsequently guide policy and other intervention instruments to encourage the regulation of health and manage population health. Namely, with the coverage of high PM2.5 and low median income scores in the areas, the fact was expected to be the most susceptible to respiratory disease with a particular emphasis on mitigation actions. The interpretability is necessary to gain the stakeholder confidence and encourage evidence-based policymaking.

It was also the reason why task-specific assessment could be developed since the ensemble-based AI modeling was combined with feature importance analysis, and spatial risk mapping. The simulation of the minimization of the exposure to the pollutants was also found as a possibility to estimate the type of improved populations health outcomes. According to the pre-empted respiratory risk associated with such training, there was observed to be a 0.8 percentage shift with a decline of 10 to 15 percent of PM2.5 that reflected the quantitative benefits of environmental intervention. This type of application proves that AI-based frameworks can be used practically when making policies and reviewing them in the context of public health.

Overall, the research results indicate that the suggested methodology results in a powerful interpretable, and practical way of environmental risk assessment. This tool is a strong decision support tool that may be adopted by policy makers because of its high productiveness, spatial visualization and capturing features. The article points out that AI-assisted solutions may revamp the procedure of correlating environmental exposures and health outcomes, enable detection of hazard spaces instead of considering and allocating resources appropriately and eventually, devise the interventions that diminish health threats among the adverse consequences.

CONCLUSION

The impact on human health through environmental pollution can be very bad and furthermore during the conventional risk assessment techniques, there are multifaceted datasets that investigate chemical and biological variables besides the demographical variables making them hard to incorporate. The paper presents a case of an artificial intelligence (AI)-driven conceptualization of environmental risk assessment that will also seek to quantify the serial percentage change in unhealthy health occurrences caused by the exposure to the pollutants. By employing machine learning, namely, random forest, gradient boosting and artificial neural networks, we processed multisource data which included air, water and soil, pollution levels, regional health records and demographic variables. The identification of vital environmental and socio-economic predictors using feature selection algorithms allowed the prediction of health risks at a population level. The proposed AI model was more precise and resilient than the traditional statistical instruments and provided convenient data with regard to the risky territories and susceptible groups. Through our study, we also indicatively refer to the AI opportunity of enhancing environmental health monitoring in fostering regulatory activities and evidence-based policymaking. Also amid these advances, there are still problems such as heterogeneity of data, lack of temporary resolution, and explainability of AI models. Future directions include ensuring that real-time environmental monitoring is in place, building explainable AI models and enhancing circularity predictability to include new pollutants.

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