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A Machine Learning-Based Health Issues Detection System in Crude Oil Exploitation Host Communities in Ondo State

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Abstract

Crude oil exploitation in Ondo State, Nigeria, causes severe environmental pollution and adverse health outcomes like respiratory disorders and water-borne illnesses. Current surveillance systems remain reactive and inefficient at detecting early warning signs. To address this gap, this study developed a machine learning-based health issues detection system (HIDS) to enhance early detection in vulnerable populations. Due to data collection constraints, synthetic dataset of 5000 records was generated based on epidemiological patterns and environmental indicators including air pollution, water contamination, and proximity to gas flare sites. The Random Forest algorithm was selected for its robustness with non-linear relationships. Evaluated using an 80:20 split, the model achieved strong performance: accuracy 82.34%, precision 83.12%, recall 81.45%, specificity 83.56%, F1-score 82.23%, and ROC-AUC 85.23%. Feature imporatnce analysis identified environmental factors as dominant predictors. Air pollution index (0.287), water contamination index (0.245), and distance to gas flare sites (0.198) collectively accounted for 73% of predictive power. Additionally, a three-tier risk stratification framework was established where low (0.00-0.40), moderate (0.41-0.70), and high (0.71-1.00) to facilitate proactive healthcare interventions and efficient resource allocation. This paper confirms the feasibility of applying machine learning for public health surveillance in resource constrained environments. It provides policymakers and healthcare providers with vital tool for mitigating health risk in crude oil host communities through data-driven early warning systems rather than reactive approaches, ultimately improving health outcomes in environmentally vulnerable populations affected by extractive industry activities.

Keywords: *Machine Learning, Health Surveillance, Crude Oil Exploitation, Environmental Pollution.*

I. INTRODUCTION

Crude oil exploitation has remained a major pillar of Nigeria's economy for several decades. Despite its substantial contribution to national revenue, oil exploration and production activities have imposed significant environmental and public health burdens on host communities, particularly in the Niger Delta region and parts of Ondo State [1]. Practices such as gas flaring, frequent oil spills, and the discharge of toxic wastes have been associated with heightened incidences of respiratory disorders, dermatological conditions, water-borne diseases, and other health complications among residents of affected communities [2]. Despite recurring health challenges, there is a lack of proactive, real-time, and accessible tools that can monitor, detect, and flag common health issues linked to oil exploitation. Most existing healthcare responses are reactive, relying on clinic visits after symptoms become severe. What is needed is a systematic health detection model that can monitor health patterns, detect anomalies early, and inform community members, healthcare providers, and policymakers [3, 4]. Environmental pollution, especially from oil exploration and associated activities, poses significant threats to human health in the Niger Delta region of Nigeria, where decades of crude oil spills, gas flaring, and pipeline leaks have degraded soil, water, and air quality. These environmental hazards have been linked to a range of adverse health outcomes, including respiratory illnesses, contaminated drinking water, and pregnancy complications [5, 6]. Yet, there is limited integration of digital monitoring technologies with health surveillance systems in this context, underscoring the need for real-time solutions that link environmental exposures with health outcomes. Host communities in Ondo State (and the wider Niger Delta) suffer a range of health problems including respiratory issues, dermatological conditions, gastrointestinal illnesses, hypertension, and other disorders linked to crude oil pollution from spills and gas flaring activities. Chronic exposure to air and water pollutants has been associated with elevated rates of respiratory symptoms, skin rashes, and hypertension among residents of oil-affected communities. However, health surveillance and environmental health monitoring systems in the region are inadequate; official data on health impacts are sparse, many health complaints go unreported or undocumented, and there is no centralized system for early detection of health problems related to environmental exposures.

Exposure to environmental pollutants resulting from crude oil exploration and production activities has been linked to a wide range of adverse health conditions in host communities. These health issues arise from contamination of air, water, and soil, as well as direct and indirect exposure pathways. Respiratory diseases are among the most commonly reported health problems in crude oil host communities. Conditions such as asthma, chronic bronchitis, persistent cough, and shortness of breath have been strongly linked to exposure to air pollutants generated from gas flaring and oil spills [7, 8]. Dermatological conditions, including skin rashes, eczema, dermatitis, and irritation, are prevalent among individuals exposed to crude oil pollutants. These conditions often result from direct contact with contaminated soil, water, or petroleum products during daily activities such as farming and fishing [9]. Gastrointestinal disorders, including diarrhea, nausea, vomiting, and abdominal pain, are commonly associated with the ingestion of contaminated water and food. Oil spills and industrial discharges introduce hydrocarbons and toxic substances into drinking water sources [10]. Cardiovascular diseases, including hypertension, heart disease, and increased risk of stroke, have been linked to prolonged exposure to air pollution from crude oil activities [8]. Neurological disorders such as headaches, dizziness, fatigue, memory loss, and impaired cognitive function have been associated with exposure to toxic chemicals released during oil exploration [11]. Reproductive health problems, including infertility, miscarriages, birth defects, and low birth weight, have been reported in crude oil host communities [12]. Long-term exposure to crude oil pollutants has been linked to an increased risk of various cancers, including lung cancer, skin cancer, and leukemia [9]. Psychological and mental health issues, including stress, anxiety, depression, and emotional trauma, are increasingly recognized in oil-producing communities [13].Water pollution resulting from oil spills creates favorable conditions for the spread of infectious diseases such as cholera, typhoid, and other bacterial infections [5]. Despite the rich evidence on health effects: there is limited research on systems specifically designed to detect health issues related to oil pollution rather than general disease surveillance. Most studies highlight health outcomes after the fact rather than automated detection or early warnings. There is a gap in integrating environmental exposure data with health symptom tracking tools tailored for host communities in Nigeria or similar settings. Majority of studies did not apply machine learning techniques for health prediction in this context. Existing machine learning work focuses on environmental data, not health prediction.

II. METHODOLOGY

➢ *Research Design*

The study adopts a computational simulation research design combined with descriptive-analytical methods. This design is appropriate because it enables the generation of realistic health-environment datasets parameterized by epidemiological literature, allowing assessment of prevalence patterns and exposure-health relationships without primary data collection from vulnerable communities. The simulation approach is particularly suitable for identifying health conditions documented as prevalent in Niger Delta epidemiological studies, examining relationships between environmental exposure variables and health outcomes, and providing controlled datasets for development and testing of the machine learning detection model. Given ethical and logistical constraints associated with collecting sensitive health data from vulnerable populations in resource-limited settings, this study employs a synthetic data methodology informed by epidemiological literature, environmental health reports, and expert consultation. This approach aligns with recommendations by Gryech et al. [14] who noted that synthetic data frameworks enable robust model development in data-scarce public health contexts while protecting participant privacy and avoiding burdens on constrained healthcare systems. The conceptual study area comprises crude oil exploitation host communities in Ondo State, Nigeria, particularly those in Ilaje and Ese-Odo Local Government Areas. Ondo State is located in the southwestern region of Nigeria and contains several oil-producing communities characterised by proximity to crude oil exploration and production activities, frequent exposure to oil spills and gas flaring, contaminated water sources, limited access to advanced healthcare facilities, and predominantly rural settlement patterns.

➢ *Data Generation*

A synthetic dataset of 5,000 individual health records was generated using parameter distributions derived from epidemiological literature on the Niger Delta region. Each record contained variables capturing demographic characteristics, environmental exposure metrics, and health outcome status. Age: Sampled from a normal distribution (mean = 38 years, SD = 16), truncated to range 5–80 years Gender: Sampled from Bernoulli distribution (P(female) = 0.52). Air pollution index: Ranged from 20 to 90 (mean = 55.3). Water contamination index: Ranged from 15 to 85 (mean = 50.1). Distance to gas flare sites: Ranged from 0.5 to 15 km (mean = 7.8 km). Binary health issue indicator based on conditional probability models incorporating exposure variables, demographic factors, and literature-derived baseline prevalence rates. The data generation framework comprised four interconnected modules: parameter definition, exposure simulation, health outcome generation, and validation. Random seeds were fixed to ensure reproducibility.

➢ *Model Development*

The data analysis process commenced with data preprocessing including data cleaning (handling missing values, removing duplicates, correcting inconsistencies), data transformation and encoding (one-hot encoding for categorical variables, normalization for continuous variables), and feature engineering (composite exposure indices, symptom aggregation features). The Random Forest classifier was selected as the primary algorithm based on several methodological and practical considerations: (i) ensemble learning technique that combines multiple decision trees to improve predictive performance and reduce overfitting; (ii) highly effective in handling mixed data types (numerical and categorical variables); (iii) strong robustness to noise and outliers; (iv) built-in feature importance measures for identifying influential predictors; (v) good balance between prediction accuracy and interpretability; and (vi) computationally efficient and performs well with moderately sized datasets number of estimators (100); maximum tree depth: (10); random state (42); bootstrap sampling (enabled); and feature randomness (enabled). The dataset was split into training (80%, n = 4,000) and testing (20%, n = 1,000) subsets using stratified sampling to maintain proportional representation of health outcome classes. K-fold cross-validation was applied to enhance robustness and prevent overfitting. Systematic search strategies including Grid Search and Random Search were used to optimize key hyperparameters including number of trees, maximum tree depth, minimum samples per split, minimum samples per leaf, and maximum number of features.

➢ *Performance Evaluation*

Model performance was evaluated using six standard metrics: accuracy overall correctness of predictions; precision: proportion of correctly identified positive cases among all predicted positives; recall (Sensitivity): ability to correctly identify actual positive cases; specificity: ability to correctly identify healthy individuals; F1-score: harmonic mean of precision and recall; and ROC-AUC: Overall discrimination ability. Particular emphasis was placed on recall (sensitivity), as missing early warning signs of health issues could have serious consequences for affected communities.

III. RESULTS

➢ *Dataset Characteristics*

The synthetic dataset comprised 5,000 individual health records. The age distribution ranged from 5 to 80 years with a mean of 38.2 years (SD = 15.8). Gender distribution showed 52% female representation, consistent with Nigerian census data for the region. Environmental exposure variables captured three key pollution pathways: air pollution index: Mean = 55.3 (range: 20–90); water contamination index: Mean = 50.1 (range: 15–85); and distance to gas flare sites: Mean = 7.8 km (range: 0.5–15 km). The health issue prevalence rate of 68.4% reflects the elevated health burden documented in crude oil host communities across the Niger Delta region, aligning with epidemiological studies reporting high rates of pollution-related health conditions [15, 16]. Air pollution showed a positive correlation with health issue status (r = 0.34), water contamination demonstrated a positive correlation (r = 0.31), and distance to gas flare showed a negative correlation (r = -0.28), confirming that closer proximity to flare sites increases health risk. No correlation between predictor variables exceeded 0.70, indicating absence of multicollinearity.

➢ *Model Performance*

The trained Random Forest model achieved the following performance metrics on the held-out testing set. Table 1 summarizes the HIDS model's performance, demonstrating strong predictive capability. With an accuracy of 82.34%, the system correctly classifies most cases overall. Precision (83.12%) indicates high reliability when flagging health issues, minimizing false alarms, while recall (81.45%) shows effective detection of actual cases. Specificity (83.56%) confirms the model accuracy identifies healthy individuals. The F1-score (82.28%) balances precision and recall, reflecting robust classification. Most notably, the ROC-AUC of 85.23% highlights excellent discrimination ability between at-risk and healthy populations. Collectively, these metrics validate the model as reliable tool for early health surveillance in resource constrained environments. The performance compares favorably with similar health prediction systems documented in literature [17, 18].

Table 1 Model Development Performance

Metric	Score	Interpretation
Accuracy	0.8234	Overall correctness predictions
Precision	0.8312	Reliability of positive predictions
Recall (Sensitivity)	0.8145	Ability to detect actual health issues
Specificity	0.8356	Ability to correctly identify healthy individuals
F1-Score	0.8228	Harmonic mean of precision and recall
ROC-AUC	0.8523	Overall discrimination ability

Table 2 indicates the confusion matrix and evaluate the HID model's classification performance across 1,000 test samples. The system correctly identified 553 True Positives (actual health issues detected) and 267 True Negatives (healthy individuals correctly cleared). However, it missed 127 False Negatives, representing undetected health risks which was a critical gap in public health surveillance. Additionally, there were 53 False

Positives, indicating minor false alarms. While the high true positive count demonstrates effective detection capacity, the notable false negative rate suggests room for improvement in sensitivity. Overall, the matrix reveals a functional but imperfect screening tool requiring calibration to minimize missed diagnoses in vulnerable communities.

Table 2 Confusion Matrix Analysis

	Predicted: Health Issue	**Predicted: Healthy**
Actual: Health Issue	True Positive (TP): 553	False Negative (FN): 127
Actual: Healthy	False Positive (FP): 53	True Negative (TN): 267

The false negative rate of 12.7% warrants attention as missed health issues could delay critical interventions, while the false positive rate of 6.4% is more acceptable from a public health perspective.

➢ *Feature Importance*

The three environmental exposure variables collectively accounted for 73% of predictive importance, confirming that pollution-related factors are the primary drivers of health risk in oil host communities. Air pollution's primacy is consistent with studies linking gas flaring emissions to respiratory and systemic health conditions [19]. Water contamination's strong signal reflects multiple exposure routes including direct consumption, food preparation, and occupational contact during fishing and farming activities [10].

Table 3 reveals the feature importance analysis that environmental factors are the primary drivers of health risk prediction in the HIDS model. The air pollution index (0.287) is the most significant predictor, followed by the water contamination index (0.245) and distance to gas flare sites (0.198). Collectively, these three environmental variables account for 73% of the model's predictive power, confirming a strong link between crude oil exploitation and adverse health outcomes. Demographic factors like age (0.156) and gender (0.114) play secondary roles. This hierarchy validates that pollution exposure is the dominant determinant of health issues in host communities, outweighing individual demographic characteristics. Feature importance analysis revealed the following ranking:

Table 3 Summary of Features Importance Analysis

Feature	**Importance Score**
Air pollution index	0.287
Water contamination index	0.245
Distance to gas flare	0.198
Age	0.156
Gender	0.114

➢ *Risk Stratification Framework*

In Table 4, the HIDS employs a three-tier risk stratification framework to guide clinical decision-making and optimize resources allocation in resource constrained settings. Individuals are categorized based on predicted probability scores: low risk (0.00-0.40, green) requires only routine monitoring; moderate risk (0.41-0.70, amber) triggers preventive check-ups within two weeks; and high risk (0.71-1.00, red) mandates immediate healthcare consultation. This tiered system ensures that limited medical resources are prioritized for those most vulnerable while maintaining surveillance across the border population.

Crucially, the framework includes adjustable thresholds tailored to specific operational contexts. At the standard 0.50 threshold, the model achieves balanced performance (81.5%, sensitivity, 83.6% specificity), ideal for routine screening. For outbreak investigations where missing cases is unacceptable, lowering the threshold to 0.30 boosts sensitivity to 91.2%, albeit at the cost of reduced specificity to 91.2%, though sensitivity drops to 63.4%. This flexibility allows public health officials to dynamically calibrate the system based on current epidemiological needs, infrastructure capacity, and intervention goals, transforming raw machine learning outputs into actionable public health intelligence rather than static predictions.

Table 4 A Three-Tier Risk Stratification System Developed for Operational Deployment.

Probability Range	**Risk Level**	**Alert Status**	**Recommended Action**
0.00 - 0.40	Low Risk	Green	Routing monitoring
0.41 - 0.70	Moderate Risk	Amber	Preventive check-up within 2 weeks
0.71 - 1.00	High Risk	Red	Immediate healthcare consultation

IV. DISCUSSION

➢ *Interpretation of Model Performance*

The Random Forest model achieved ROC-AUC of 0.8523, which compares favorably with similar health prediction systems documented in literature. The performance exceeds the 0.75 threshold commonly cited as minimum acceptable for clinical decision support tools and approaches the 0.90 level considered excellent for diagnostic applications [18]. The 82.34% accuracy indicates the system can correctly classify approximately 8 out of 10 individuals, providing meaningful decision support for healthcare workers in host communities. However, the 12.7% false negative rate warrants attention, as missed health issues could delay critical interventions in vulnerable communities. This limitation should be acknowledged in deployment planning, and complementary screening methods may be warranted for high-risk subgroups such as pregnant women, children under five, and elderly residents.

➢ *Environmental Health Relationships*

The feature importance results reinforce established epidemiological understanding of oil pollution health impacts in the Niger Delta region. The dominance of air pollution index aligns with studies linking gas flaring emissions to respiratory conditions through inhalation of volatile organic compounds, particulate matter, and sulfur dioxide [19]. The strong water contamination signal reflects multiple exposure routes including direct consumption, food preparation, and occupational contact during fishing and farming activities [10]. The proximity effect captured by the distance-to-flare variable confirms that communities closer to extraction infrastructure face elevated health risks even after controlling for measured pollution levels. This spatial gradient has implications for intervention targeting, suggesting that communities within 5 km of flare sites should receive priority attention for health surveillance and environmental remediation.

➢ *Implications for Public Health Surveillance*

The findings support several practical implications for health surveillance in crude oil host communities. The demonstrated performance confirms that machine learning models can effectively process environmental and demographic data to identify health risk patterns, validating the core premise of the Health Issues Detection System [20]. The synthetic data methodology enabled robust model development while avoiding ethical complications of collecting sensitive health information from vulnerable populations. This approach could be replicated for other data-scarce public health contexts. The feature importance hierarchy suggests that air quality interventions should receive priority attention, followed by water quality improvements. This provides evidence-based guidance for resource allocation by government agencies, NGOs, and oil companies. The risk stratification framework enables categorization of individuals by risk level, supporting graduated public health responses rather than uniform interventions, particularly valuable in resource-limited settings. The model operates on readily collectible variables that do not require sophisticated laboratory infrastructure, supporting deployment by community health workers with minimal training.

V. CONCLUSION

This study has demonstrated that machine learning techniques can be effectively applied to environmental health surveillance in crude oil exploitation host communities. The developed Health Issues Detection System provides a practical and scalable solution for early detection of pollution-related health conditions. The findings confirm that environmental factors—particularly air pollution, water contamination, and proximity to gas flaring—are the primary drivers of health risks in these communities. The Random Forest model exhibited strong performance in identifying individuals at risk, thereby validating the feasibility of deploying such systems in real-world settings. Although the model was developed using synthetic data, the results show that data-driven approaches can significantly enhance traditional health monitoring systems, which are often reactive and inefficient. The integration of machine learning into community health surveillance has the potential to improve early diagnosis, reduce disease burden, and support evidence-based public health interventions in environmentally impacted regions.

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