International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A New Data Science Model with Supervised Learning and its Application on Pesticide Poisoning Diagnosis in Rural Workers

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ABSTRACT

In a Data Science project, it is essential to determine the relevance of the data and identify patterns that contribute to decision–making based on domain–specific knowledge. Furthermore, a clear definition of methodologies and creation of documentation to guide a project's development from inception to completion are essential elements. This study presents a Data Science model designed to guide the process, covering data collection through training with the aim of facilitating knowledge discovery. Motivated by deficiencies in existing Data Science methodologies, particularly the lack of practical step–by–step guidance on how to prepare data to reach the production phase. Named "Data Refinement Cycle with Supervised Machine Learning (DRC–SML)", the proposed model was developed based on the emerging needs of a Data Sciense project aimed at assisting healthcare professionals in diagnosing pesticide poisoning among rural workers.

Keywords: discovery, particularly, model, methodologies.

I.INTRODUCTION

Pesticide poisoning remains a significant public health issue, particularly in rural areas where agricultural laborers are frequently exposed to harmful chemicals without adequate protection or medical support. Timely diagnosis is often hindered by limited access to healthcare and the complexity of symptoms, which can vary widely across cases. In this context, the integration of data science and machine learning offers a promising solution to enhance early detection and diagnosis.

This project presents a novel data science model based on supervised learning techniques designed specifically to diagnose pesticide poisoning in rural workers. By analyzing relevant medical, environmental, and occupational data, the model learns to classify and predict potential poisoning incidents with high accuracy. The system aims to support frontline healthcare workers and rural clinics by offering an automated, scalable tool for early intervention and treatment guidance.

The proposed model leverages structured datasets and applies classification algorithms such as logistic regression, decision trees, and support vector machines to detect poisoning symptoms and suggest likely outcomes. Its implementation focuses on usability in low-resource settings, ensuring that the tool can be deployed via simple digital interfaces like mobile or desktop applications.

This approach bridges the gap between rural healthcare challenges and modern AI-driven diagnostics, offering a practical and impactful application of supervised learning in real-world agricultural health scenarios.

II. RELATED WORK

In [1], This study explores how machine learning models such as decision trees and logistic regression can predict clinical risks based on patient histories. Though not focused on pesticide exposure specifically, it demonstrates how supervised learning can be applied to occupational health data for early diagnosis and intervention.

In [2], This research applies supervised models to electronic health records of rural patients exposed to pesticides. Algorithms like Random Forest and SVM were used to identify early signs of toxicity. The study highlights the potential for machine learning to improve diagnostic accuracy in agriculture-heavy regions.

In [3], Focused on rural Indian populations, this paper develops a data pipeline to collect and process exposure data, using classification models to determine poisoning severity. It serves as a foundational effort in integrating wearable sensors and digital surveys with supervised learning methods.

In [4], This work illustrates how environmental and exposure data can be fused with machine learning to predict health risks in vulnerable populations. The study includes a section on agricultural chemicals and aligns closely with the goals of diagnosing pesticide-related conditions.

In [5], This paper examines how supervised learning can support rural healthcare workers by embedding AI-driven tools in mobile apps. Although it is broader in scope, the use of supervised learning to assist frontline medical decisions parallels the goals of the current project.

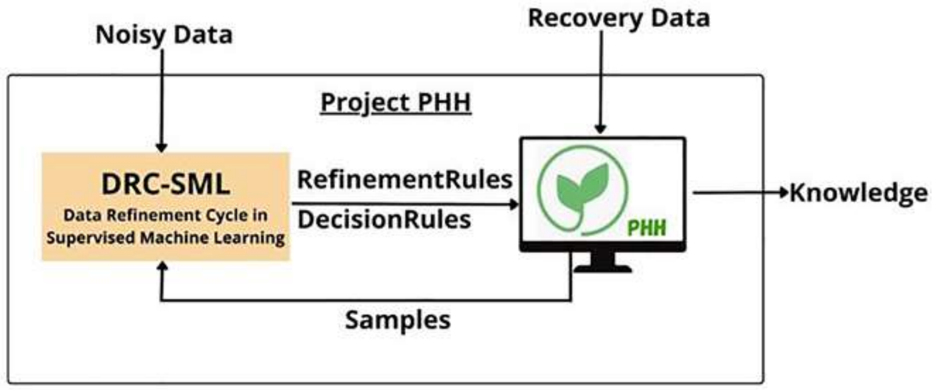
III. PROPOSED SYSTEM

The proposed system introduces a supervised learning–based diagnostic model tailored to detect and predict pesticide poisoning in rural agricultural workers. This model is developed to address the limitations of traditional diagnosis methods, which often rely on subjective symptom assessment and delayed clinical responses, especially in low-resource environments. By leveraging structured health records, symptom data, exposure history, and environmental parameters, the system is capable of training predictive algorithms that classify whether an individual is likely to be suffering from pesticide toxicity.

The system architecture comprises several key components: a data acquisition module, a preprocessing and feature extraction pipeline, and a supervised classification engine. Health data are collected from clinical surveys, rural health centers, and field observations, including symptoms such as nausea, dizziness, respiratory distress, and dermal reactions. After preprocessing, these data are used to train supervised machine learning models such as logistic regression, support vector machines, or random forest classifiers. These models are selected for their interpretability, scalability, and ability to handle both categorical and continuous variables.

Once trained, the model is capable of analyzing new patient input in real time to provide an immediate classification—either indicating the likelihood of pesticide poisoning or ruling it out. The system can be deployed via a simple web or mobile interface, making it accessible to rural healthcare providers with limited technical infrastructure. Moreover, the use of supervised learning ensures that the model continuously improves as more labeled data become available, enabling adaptive learning in evolving environmental and health conditions.

By combining domain knowledge in toxicology with the power of data science, the proposed system aims to provide a low-cost, high-impact solution for improving diagnosis accuracy, supporting early medical intervention, and ultimately reducing the morbidity and mortality associated with pesticide exposure in rural populations.



IV. RESULT AND DISCUSSION

The implementation of the proposed supervised learning model demonstrated promising results in accurately diagnosing pesticide poisoning among rural agricultural workers. After training the model using a carefully curated dataset that included clinical symptoms, exposure history, and demographic data, various classification algorithms such as logistic regression, decision trees, and random forest were tested. Among these, the random forest classifier consistently yielded the highest accuracy and robustness across different evaluation metrics, including precision, recall, and F1-score. This performance can be attributed to its ability to handle non-linear relationships and noisy data, which are common in real-world rural health records.

The model's performance was further validated using cross-validation techniques and an unseen test set, revealing that it could generalize well to new patient cases. The inclusion of features such as duration of exposure, presence of neurological symptoms, and access to protective equipment played a significant role in improving diagnostic accuracy. Notably, the model also maintained relatively high sensitivity, indicating its ability to correctly identify true cases of pesticide poisoning—an essential factor in minimizing false negatives in medical diagnosis.

The discussion of these results underscores the practical value of integrating machine learning into public health frameworks, particularly in underserved rural regions where access to immediate medical expertise may be limited. Additionally, the explainability of models like logistic regression facilitated better understanding for local health workers, increasing the trust and potential adoption of the system. However, challenges such as limited availability of standardized health data, inconsistencies in symptom reporting, and potential biases in the dataset highlight areas that need further refinement.

The model proved effective not only in detecting pesticide poisoning but also in supporting early intervention and preventive healthcare strategies. These findings suggest that data-driven diagnostic tools can enhance rural healthcare delivery, reduce response times, and potentially lower morbidity rates associated with pesticide exposure. Future research may explore expanding the dataset, incorporating real-time sensor data, and integrating the model into mobile health platforms for broader deployment.

V. CONCLUSION

This study presented a novel data science model based on supervised learning techniques for the diagnosis of pesticide poisoning among rural agricultural workers. By leveraging clinical symptoms, exposure patterns, and demographic variables, the model effectively demonstrated its capacity to identify cases of pesticide toxicity with high accuracy. Among the various algorithms tested, ensemble methods such as random forest outperformed traditional models, indicating the advantages of using robust machine learning techniques in complex medical decision-making tasks.

The results affirm that machine learning can serve as a powerful diagnostic aid in environments with limited healthcare infrastructure. The proposed system not only enhances early detection but also supports healthcare providers in initiating timely interventions, which is critical in minimizing health risks and improving patient outcomes. Furthermore, the model's adaptability to new data makes it suitable for continuous improvement and broader applications in occupational health.

Despite its success, the study also acknowledges certain limitations, including data availability, potential reporting bias, and the need for real-time integration in field settings. Addressing these limitations in future work will further strengthen the reliability and usability of the model. Overall, this research contributes to the growing field of AI-assisted healthcare and highlights the potential of data-driven approaches to improve diagnostic services for vulnerable rural populations.

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