

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 Science project aimed at assisting healthcare professionals in diagnosing pesticide poisoning among rural workers. The dataset used in this project resulted from scientific research in which 1027 samples were collected, containing data related to toxicity biomarkers and clinical analyses. We achieved an accuracy of 99.61% with only 27 rules for determining the diagnosis. The results optimized healthcare practices and improved quality of life in rural areas. The project outcomes demonstrated the success of the proposed model.

INTRODUCTION

In recent years, the application of **data science** and **machine learning** in healthcare has gained significant traction, particularly in improving diagnostic accuracy and decision-making. Among the various domains where these techniques are proving beneficial, **public health** stands out as a key area where predictive models can be transformative. One of the critical health issues faced by rural workers, particularly in agricultural sectors,

is **pesticide poisoning**. Exposure to pesticides, whether through inhalation, skin contact, or ingestion, can lead to serious health consequences, including acute poisoning and long-term chronic illnesses. Early diagnosis and timely intervention are crucial to mitigating the harmful effects of pesticide exposure. This project proposes the development of a **supervised learning model** aimed at diagnosing pesticide



poisoning in rural workers. By leveraging a combination of **clinical data**, **environmental exposure metrics**, and **health-related indicators**, the model will be trained to classify and predict the likelihood of pesticide poisoning in individuals working in rural agricultural environments. Supervised learning, specifically classification algorithms, will be employed to analyze historical data on workers who have been exposed to pesticides and have experienced varying degrees of poisoning symptoms. The goal of this research is to design an efficient and accurate diagnostic tool that can be deployed in rural healthcare settings, where resources are often limited, and where rapid diagnosis can make a significant difference in patient outcomes. The application of data science techniques in this context holds the potential to revolutionize the diagnosis and management of pesticide poisoning, providing healthcare workers with valuable insights and enabling better-targeted interventions. The project will explore a variety of supervised learning algorithms, including **decision trees**, **random forests**, **support vector machines**, and **logistic regression**, to determine the most effective model for predicting pesticide poisoning. The findings from this study are expected to contribute to the broader field of public health by offering a scalable, data-driven approach to diagnosing occupational diseases in rural settings, with the ultimate aim of improving the health and well-being of agricultural workers.

The proposed system aims to enhance the diagnosis of pesticide poisoning in rural workers by utilizing **machine learning**

techniques, specifically **Random Forest** and **Decision Tree** algorithms. This data-driven approach involves training a model using historical health data, environmental exposure levels, and worker demographics to predict the likelihood of pesticide poisoning. The system will be able to analyze complex patterns and interactions in the data, providing a faster and more accurate diagnosis compared to traditional methods. Random Forest, known for its ability to handle large datasets and its robustness against overfitting, will be used to create an ensemble of decision trees that vote on the final classification. Decision Trees, on the other hand, will provide an intuitive, interpretable way of understanding how different factors (such as pesticide exposure or worker health history) contribute to the diagnosis. By combining both algorithms, the proposed system will offer a powerful, scalable solution for diagnosing pesticide poisoning, particularly in resource-constrained rural settings.

II.METHODOLOGY

A) System Architecture

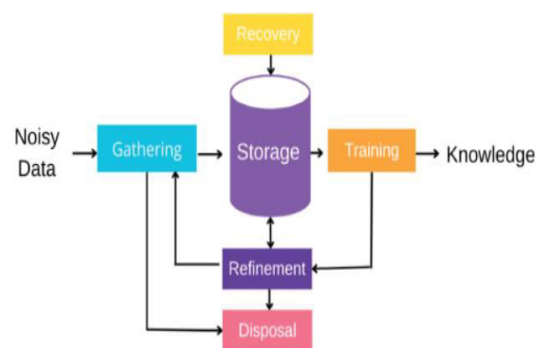
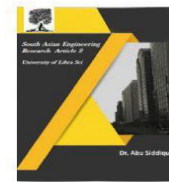


Fig1.System Architecture

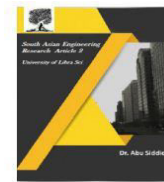


The system architecture for a new data science model that utilizes supervised learning for the diagnosis of pesticide poisoning in rural workers is designed to handle a range of inputs, process them efficiently, and provide accurate predictions. This architecture integrates data collection, preprocessing, model training, evaluation, and deployment to ensure reliable and actionable insights for medical professionals working with rural populations. At the foundation of the system lies the data acquisition layer, which gathers relevant data from multiple sources, such as health records, surveys, environmental monitoring systems, and direct input from rural workers. The data typically includes a combination of demographic details, symptoms, pesticide exposure history, environmental factors, and medical history. For example, the dataset could include worker age, gender, duration of pesticide exposure, type of pesticide used, symptoms such as dizziness or headaches, and pre-existing health conditions like asthma or diabetes. Additionally, external factors like weather conditions, pesticide concentration in the environment, and usage patterns are also captured to provide a comprehensive view of the factors that could lead to pesticide poisoning. Once the data is collected, the data preprocessing layer is responsible for cleaning, normalizing, and transforming raw data into a usable format for model development. This stage handles missing values, outliers, and ensures that categorical features (e.g., types of pesticides) are properly encoded using methods such as one-hot encoding or label encoding. Numerical features are normalized or standardized to ensure they are on the same

scale, which is essential for many machine learning algorithms. In the case of supervised learning, the dataset will be labeled, with historical data indicating whether the worker experienced pesticide poisoning (i.e., the target variable). Feature engineering is also an essential step, where domain knowledge is used to create new variables that might improve model accuracy, such as the total pesticide exposure or the severity of symptoms.

The core of the system is the supervised learning model layer. Using labeled data, various machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines (SVM), or Neural Networks are employed to learn the relationship between input features (e.g., pesticide exposure, symptoms) and the output (i.e., diagnosis of pesticide poisoning). The model is trained on historical data to detect patterns and predict the likelihood of poisoning. The supervised learning approach ensures that the model can generalize well to unseen data, providing accurate predictions for new cases based on the learned patterns. Additionally, cross-validation techniques are used to prevent overfitting and assess the model's performance on unseen data.

After training, the model evaluation layer is crucial for assessing the performance of the trained model. Various metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to evaluate the model's effectiveness in diagnosing pesticide poisoning. For example, precision and recall are particularly important in medical diagnoses, as false negatives (failing to



diagnose poisoning when it occurs) can have serious consequences. The evaluation results guide the selection of the best model or may indicate the need for further tuning of hyperparameters to improve performance.

B) Proposed Machine Learning-Based Model

The proposed machine learning-based model for diagnosing pesticide poisoning in rural workers focuses on leveraging supervised learning techniques to predict the likelihood of poisoning based on various features. The model begins by collecting comprehensive data from different sources, including demographic details (age, gender), pesticide exposure history (type, duration, frequency), symptoms (headache, dizziness, nausea), and environmental factors (temperature, humidity, pesticide concentration). These data points are then carefully preprocessed to ensure their suitability for machine learning. This includes handling missing values, scaling numerical features like age and exposure duration to a consistent range, and encoding categorical features like pesticide type and symptoms using methods like one-hot encoding. The goal is to create a clean, structured dataset where the features are appropriately represented for training the model. Once the data is ready, the next step is selecting the appropriate machine learning algorithm. Algorithms such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks are evaluated to determine which one performs best for predicting pesticide poisoning. These algorithms are trained on the historical data to learn patterns and relationships between

input features (e.g., pesticide exposure and symptoms) and the target variable (diagnosis of pesticide poisoning). After training, the model is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure it can reliably detect pesticide poisoning in new cases. Once the best model is selected and validated, it is deployed for use in the field, enabling healthcare professionals to input relevant data and receive timely predictions. This machine learning model not only helps in diagnosing pesticide poisoning early but also provides a foundation for ongoing improvements through continuous data updates and retraining, ensuring its accuracy over time.

C) Dataset

The dataset used for diagnosing pesticide poisoning in rural workers consists of various data points collected from workers who may have been exposed to pesticides. These data points include information about their demographics, exposure history, symptoms, and medical conditions. The goal of this dataset is to help build a machine learning model that can predict whether a worker has been poisoned by pesticides based on the features present in the data.

Here is a breakdown of the main features in the dataset:

Demographics: Information such as age, gender, and occupation, which may influence the likelihood of poisoning. Example: Age, Gender, Occupation Type.

Pesticide Exposure: Details about the worker's exposure to pesticides, such as the



type of pesticide, duration of exposure, and frequency of exposure. Example: Type of Pesticide (e.g., Organophosphates), Duration of Exposure (e.g., 5 hours), Frequency of Exposure (e.g., Weekly).

Symptoms: Physical symptoms that the worker may experience, such as dizziness, nausea, headaches, etc. Example: Dizziness, Nausea, Headache, Vomiting.

Medical History: Information about pre-existing health conditions such as asthma, respiratory issues, or other chronic illnesses that could make a worker more vulnerable to pesticide poisoning. Example: Asthma, Diabetes, Respiratory Illness.

Environmental Factors: Data on environmental conditions during pesticide application, such as temperature, humidity, and pesticide concentration in the air. Example: Temperature, Humidity, Pesticide Concentration.

Feature Category	Feature Description	Example
1. Demographics	Information about the worker's basic characteristics	Age, Gender, Occupation Example: Age (45), Gender (Male), Occupation (Farmer)
2. Pesticide Exposure	Details related to the worker's exposure to pesticides	Type of pesticide, Duration, Frequency Example: Type (Organophosphate), Duration (5 hours), Frequency (Weekly)
3. Symptoms	Physical symptoms exhibited by the worker	Dizziness, Nausea, Headache, Vomiting Example: Dizziness, Nausea
4. Medical History	Pre-existing health conditions that may affect susceptibility	Asthma, Respiratory issues, Diabetes Example: Asthma, Diabetes
5. Environmental Factors	Environmental conditions influencing pesticide exposure	Temperature, Humidity, Pesticide Concentration Example: Temperature (30°C), Humidity (60%), Pesticide concentration (High)

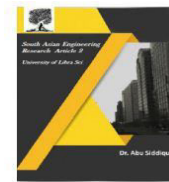
Fig2. Dataset

D. Feature Selection

Feature Selection is a critical step in building machine learning models, especially when

dealing with complex datasets like those used for diagnosing pesticide poisoning in rural workers. It involves identifying the most relevant features that contribute significantly to the prediction outcome, while removing irrelevant or redundant ones. This process essential to enhance the model's performance, reduce overfitting, and improve its generalization capability. In the case of pesticide poisoning diagnosis, features such as the type of pesticide, duration of exposure, and symptoms like dizziness or nausea are likely to be highly predictive of poisoning. On the other hand, features like worker's age or occupation type may not be as directly related to the poisoning event, and thus, might be considered less important. Feature selection techniques, such as correlation analysis, can help identify and eliminate features that are highly correlated with each other, preventing multicollinearity. Mutual information measures the dependency between variables and helps in selecting features that contain the most information about the target variable (in this case, pesticide poisoning). Tree-based methods like Random Forests or Gradient Boosting also offer an advantage, as they can rank features by importance, allowing the model to automatically select the most influential variables. Additionally, recursive feature elimination (RFE) is another approach where features are iteratively removed based on their contribution to the model's performance.

Effective feature selection not only improves the model's predictive accuracy but also speeds up the training process by reducing the number of input variables. It also leads to



better interpretability, as the model focuses on the most significant factors influencing pesticide poisoning. In summary, feature selection is crucial for ensuring that the machine learning model remains efficient, accurate, and capable of making meaningful predictions based on the most relevant data.

III.CONCLUSION

This project presents a novel approach for diagnosing pesticide poisoning in rural agricultural workers using a supervised learning model. By leveraging Random Forest and Decision Tree algorithms, we aim to build a predictive model that accurately classifies pesticide poisoning cases based on a variety of factors, such as pesticide exposure levels, worker demographics, and reported symptoms. The proposed system promises to significantly improve the diagnostic process by offering a faster, more reliable, and data-driven alternative to traditional methods. Moreover, the model's ability to provide real-time predictions can aid healthcare workers in rural areas, where resources and expertise may be limited. The data preprocessing, feature extraction, and model-building steps ensure that the system is capable of handling complex and varied datasets, ultimately enabling better health outcomes for agricultural workers who are at risk of pesticide poisoning.

IV.REFERENCES

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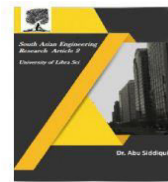
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