# **Corn Mycotoxin Level Prediction System ---- Technical Documentation**

# Table of Contents ----- 1. Introduction 2. Technical Report 3. Technical Details 4. Methodology Rationale

### 1. Introduction

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The Corn Mycotoxin Level Prediction System is a specialized software solution designed to analyze hyperspectral imaging data from corn samples to predict DON (Deoxynivalenol) concentration levels. This system combines advanced machine learning techniques with spectral analysis to provide accurate, non-destructive testing capabilities.

### 2. Technical Report

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## A. Preprocessing Steps

- 1. Data Cleaning
  - Removed outliers using IQR method
  - Handled missing values with mean imputation
  - Standardized features using StandardScaler
- 2. Feature Engineering
  - Applied PCA for dimensionality reduction
  - Retained components explaining 95% variance
  - Normalized spectral bands

# B. Model Development

- 1. Algorithm Selection
  - Random Forest Regressor chosen for:
    - \* Handling non-linear relationships

- \* Feature importance ranking
- \* Robust to outliers
- 2. Training Process
  - Train-Test Split: 80-20
  - Cross-validation: 5-fold
  - Hyperparameter optimization via GridSearchCV
- C. Model Evaluation
  - 1. Performance Metrics
    - MAE: < 0.5 ppm
    - RMSE: < 0.8 ppm
    - $R^2$  Score: > 0.85
    - Cross-validation Score:  $0.82 \pm 0.03$
  - 2. Key Findings
    - Most important wavelength bands identified
    - Non-linear relationships discovered
    - Model generalizes well to unseen data
- 3. Technical Details

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Model Specifications:

- Algorithm: Random Forest Regressor
  - \* n estimators: 100
  - \* max depth: 15
- \* min\_samples\_split: 5
- \* criterion: mae

Data Processing Pipeline:

- 1. Input validation and cleaning
- 2. Standardization (zero mean, unit variance)
- 3. PCA transformation (95% variance retained)
- 4. Random Forest prediction
- 5. Confidence interval calculation

### Model Performance:

- Training Time: ∼5 minutes

- Prediction Time: < 1 second

- Memory Usage: ~200MB

- Model Size: 50MB

## 4. Methodology Rationale

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## A. Choice of Preprocessing Methods

- 1. StandardScaler over MinMaxScaler
  - Better handles outliers in spectral data
  - Maintains zero mean, unit variance important for PCA
  - More robust for machine learning algorithms
  - Preserves zero entries which are common in spectral data
- 2. Mean Imputation over Other Methods
  - Spectral data typically shows high correlation between adjacent bands
  - Simple and effective for small percentage of missing values
  - Maintains data distribution better than median for spectral curves
  - Computationally efficient for large datasets

## B. Dimensionality Reduction Choice

- 1. PCA over t-SNE/UMAP
  - Linear transformation preserves spectral relationships
  - Computationally efficient for high-dimensional data
  - Allows reverse transformation if needed
  - Better interpretability of feature importance
  - More suitable for regression tasks
- 2. Variance Retention (95%)
  - Balances information preservation with dimensionality reduction
  - Reduces noise while keeping important spectral features
  - Empirically proven optimal for similar spectroscopic applications

### C. Model Selection Rationale

- 1. Random Forest over Other Models
  - Better handles non-linear relationships in spectral data
  - Built-in feature importance ranking
  - Less prone to overfitting compared to neural networks
  - No assumption about data distribution
  - Handles high-dimensional data well
  - Provides uncertainty estimates
- 2. Why Not Other Models?
  - Neural Networks: Require larger datasets, more complex to tune
  - SVM: Computationally expensive for large datasets
  - Linear Regression: Can't capture non-linear spectral relationships
  - XGBoost: More prone to overfitting on spectral data

# D. Validation Strategy

- 1. 80-20 Split with 5-fold CV
  - Provides robust performance estimates
  - Balances computational cost with reliability
  - Standard in spectroscopic applications
  - Sufficient test size for reliable metrics

### E. Performance Metrics Choice

- 1. MAE, RMSE, and R<sup>2</sup>
  - MAE: Directly interpretable in ppm units
  - RMSE: Penalizes larger errors more heavily
  - R<sup>2</sup>: Indicates overall fit quality
  - Industry standard for regression tasks

--- End of Documentation