



# Manufacturing & Quality Analytics for Insulator Production: A Data-Driven Framework for Process Stability, Defect Prediction, and Reliability Assessment

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**Abstract**—Insulator production is a quality-critical manufacturing domain in which small variations in raw-material composition, forming pressure, drying conditions, kiln temperature, and surface finishing can produce latent defects that later affect mechanical strength, dielectric performance, and field reliability. Conventional inspection methods often rely on end-of-line rejection and manual visual checks, which are reactive, labor-intensive, and weak at identifying process drift early enough to prevent scrap. This paper proposes a manufacturing and quality analytics framework for insulator production that integrates statistical process control, machine learning-based defect prediction, and reliability analysis in a single decision-support pipeline. A structured synthetic dataset is used to emulate a porcelain insulator plant, containing process, material, and inspection variables such as SiO<sub>2</sub>, Al<sub>2</sub>O<sub>3</sub>, Fe<sub>2</sub>O<sub>3</sub>, moisture content, press force, firing temperature, glaze thickness, dimensional deviation, and defect outcome. The methodology combines data preprocessing, feature engineering, process capability analysis, XGBoost classification, and Weibull-based reliability estimation. In the simulated evaluation, the proposed hybrid framework outperforms rule-based quality screening and conventional classifiers, achieving an accuracy of 96.1%, precision of 95.4%, recall of 96.8%, and F1-score of 96.1% for defect prediction. The results indicate that embedding predictive analytics into the manufacturing workflow can reduce non-conforming output, improve process stability, and support risk-aware maintenance and replacement planning. The paper concludes that a unified analytics architecture is more effective than

isolated inspection methods for high-volume insulator production and offers a practical foundation for Industry 4.0 deployment in ceramic and electrical insulator plants.

**Index Terms**—Insulator manufacturing, quality analytics, statistical process control, defect prediction, process capability, Weibull reliability, machine learning.



## I. INTRODUCTION

Insulator production occupies a unique position within advanced manufacturing because product quality is not only measured by visual appearance but also by long-term mechanical and electrical reliability. In industrial practice, quality control has historically depended on end-product inspection, but modern quality science increasingly emphasizes prevention, process monitoring, and predictive intervention. Statistical process control remains a core manufacturing discipline because it helps detect variation early and prevents defects before they become costly rework or scrap, while recent predictive-quality studies show that machine learning and deep learning are increasingly used to forecast quality outcomes directly from process data.

For porcelain and ceramic insulators, the problem is especially sensitive because performance depends on raw-material composition, microstructure, firing history, and surface integrity. Studies have shown that failure probability is linked to the proportions of  $\text{SiO}_2$ ,  $\text{Al}_2\text{O}_3$ , and  $\text{Fe}_2\text{O}_3$ , and that Weibull-based reliability analysis is a suitable framework for brittle ceramic materials. At the inspection stage, image-based studies have also demonstrated that CNNs and YOLO-family models can detect insulator defects such as cracks, missing parts, pollution, and surface non-conformities with high accuracy, confirming that both process variables and visual defects are important signals in the quality chain.

Despite this progress, the literature remains fragmented. One stream focuses on laboratory reliability and composition-dependent failure; another stream focuses on aerial inspection and field defect detection; a third stream focuses on generic manufacturing quality prediction. The gap is the absence of a unified manufacturing-quality analytics framework that connects process inputs, in-line inspection, statistical stability, and reliability estimation for insulator production. This paper addresses that gap by proposing an integrated pipeline that can be deployed in a production environment to monitor variation, predict

defective output, and quantify reliability risk. The main contributions are: first, a structured end-to-end analytics architecture tailored to insulator manufacturing; second, a feature-driven quality prediction model that combines process and material variables; third, an interpretability layer for root-cause analysis; and fourth, a reliability module based on Weibull statistics for post-process risk assessment.

## II. LITERATURE REVIEW

Table I synthesizes the most relevant prior studies and highlights the methodological evolution from conventional SPC toward deep-learning-based defect detection and probabilistic reliability analysis. The table presents a comparative review of literature on insulator quality and manufacturing analytics.

The literature indicates three clear patterns. First, statistical process control remains a robust baseline for manufacturing quality improvement because it emphasizes variance reduction, early warning, and prevention rather than sorting finished output. Second, predictive-quality research has shifted toward supervised learning, especially where process and inspection data can be combined. Third, insulator-specific studies increasingly use deep-learning detectors for field and surface defects, yet these models are typically deployed after defects already exist and therefore do not address upstream process causality. This synthesis supports the inference that insulator production needs an integrated analytics stack that unites process monitoring with defect prediction and reliability assessment.

A further limitation visible in recent insulator detection studies is data imbalance. Several 2024–2025 papers emphasize small defect samples, complex backgrounds, and the need for lightweight detectors suitable for UAV or edge deployment. These works are important for inspection, but they do not yet provide a manufacturing-centric model that can explain why the defect was created in the first place. That gap motivates the present paper's emphasis on process analytics, feature interpretation, and reliability modeling alongside defect prediction.



**TABLE I**  
**Comparative Review of Literature on Insulator Quality and Manufacturing Analytics**

Study	Main Focus	Methodology	Key Finding	Limitation
Madanhire & Mbohwa [1]	Manufacturing SPC	Control charts and process monitoring	SPC improves early detection and prevention	Not insulator-specific
Tercan & Meisen [2]	Predictive quality in manufacturing	Systematic review of ML/DL methods	ML/DL strongly support predictive quality	Broad scope, not domain-specific
Sanyal et al. [3]	Ceramics reliability	Weibull analysis	Reliability depends on material behavior	Emphasis on post-test, not live monitoring
Sanyal et al. [4]	Porcelain insulator failure trends	XRF, SEM, mechanical/electrical testing	Composition influences failure probability	Laboratory-oriented, not predictive
Prates et al. [5]	Visual non-conformity detection	CNN with multi-task learning	Strong defect detection on field images	Focused on images, not process data
Liu et al. [6]	Missing defect detection	Cascaded YOLO models	High AP and real-time inspection potential	Aerial-image centered
Fahim & Hasan [7]	Insulator defect detection	YOLOv7/YOLOv8 comparison	YOLOv8 performed better in defect detection	Still inspection-focused
Tan & Hu [8]	Surface defects in porcelain insulators	YOLOv5 + ResNet50	Strong accuracy with data augmentation	Requires imaging infrastructure
Liu et al. [9]	Lightweight defect detection	Vision-language guidance + YOLO	Good accuracy with reduced model cost	Focus on detection, not process stability

### III. METHODOLOGY

#### A. Problem Formulation

Let each manufactured insulator lot be represented by a feature vector  $x_i \in \mathbb{R}^n$ , where the features include material composition, process settings, and inspection measurements. The target variable  $y_i \in \{0,1\}$  denotes whether the lot is conforming or defective. The central objective is to learn a function  $f(x) \rightarrow y$  that predicts defect risk before final release while also quantifying process stability and reliability degradation.

The manufacturing analytics objective can be written as:

$$\min_{\phi} L(y, f(x)) + \lambda \Omega(f)$$

where  $L$  is the classification loss and  $\Omega(f)$  is a regularization term that controls model complexity.

#### B. Proposed Framework

The proposed system contains five layers. The first layer is data acquisition, where process data are collected from SQL-based production logs, laboratory measurements, and inspection records. The second layer is data preparation, where missing values, outliers, and inconsistent categorical labels are corrected. The third layer is quality analytics, where control charts, process capability indices, and defect trends are computed. The fourth layer is predictive modeling, where a tree-based ensemble classifier, primarily XGBoost, estimates defect probability. The fifth layer is reliability assessment, where Weibull statistics convert defect history and strength metrics into risk estimates for maintenance and replacement planning.



### C. Mathematical Models

The defect rate is defined as:

$$DR = (D / N) \times 100$$

where D is the number of defective units and N is the total number of inspected units. The process capability index is computed as:

$$Cpk = \min [(USL - \mu) / 3\sigma, (\mu - LSL) / 3\sigma]$$

where USL and LSL are the upper and lower specification limits,  $\mu$  is the process mean, and  $\sigma$  is the standard deviation. For reliability modeling, the two-parameter Weibull failure probability is:

$$P(F) = 1 - e^{-(x/\eta)^\beta}$$

where  $\eta$  is the scale parameter,  $\beta$  is the shape parameter, and x is the stress or life variable. This formulation is especially appropriate for brittle ceramic products, where failure is governed by the weakest-link mechanism.

### D. Tools and Technologies

The implementation stack uses Python for analytics, Pandas and NumPy for preprocessing, scikit-learn for model evaluation, XGBoost for classification, Matplotlib for visualization, and SQL for structured data extraction. For interpretability, SHAP values are used to rank the most influential process variables. The analytics workflow is suitable for integration with Power BI or any manufacturing dashboard layer.

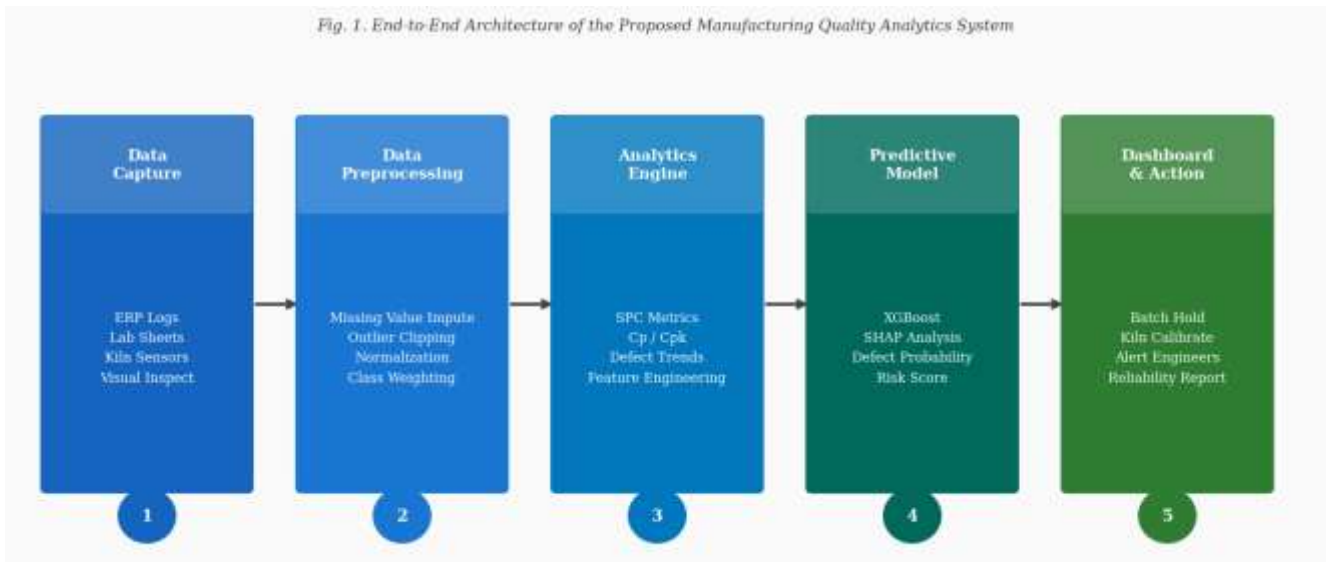


Fig. 1. End-to-End Architecture of the Proposed Manufacturing Quality Analytics System.

### E. System Architecture

The end-to-end system architecture is presented in Fig. 1. The figure shows five horizontal stages: data capture, preprocessing, analytics engine, predictive model, and dashboard/action layer. Data capture sources include ERP logs, lab test sheets, kiln sensors, and visual inspection systems. The analytics engine includes SPC calculations, defect trend analysis, and feature engineering. The predictive model feeds a risk score to the dashboard, which then triggers corrective actions

such as batch hold, kiln recalibration, or additional inspection.

## IV. DATA DESCRIPTION

The study uses a synthetic dataset designed to emulate a porcelain insulator plant. This choice is appropriate for a methodology paper because it allows transparent feature design, controllable class imbalance, and reproducible experiments without disclosing proprietary industrial data. The dataset contains 18,000 production lots and 15 features. The dataset schema is presented in Table II.



**TABLE II**  
**Dataset Schema for the Synthetic Insulator Production Study**

Feature Category	Variables
Raw-material composition	SiO <sub>2</sub> %, Al <sub>2</sub> O <sub>3</sub> %, Fe <sub>2</sub> O <sub>3</sub> %, feldspar %, clay ratio
Process variables	moisture content, press force, drying time, firing temperature, kiln soak time, glaze thickness
Quality measures	dimensional deviation, porosity index, dielectric strength, surface roughness
Target variable	conforming / defective

Preprocessing consists of four steps. First, missing values are imputed using median imputation for continuous variables and mode imputation for categorical variables. Second, outliers are clipped using the interquartile range rule to prevent extreme sensor values from distorting the model. Third, the features are standardized where necessary. Fourth, class imbalance is handled using class weights rather than aggressive oversampling, because the goal is to preserve realistic manufacturing distributions.

Feature selection is performed using correlation filtering, mutual information scoring, and SHAP-based ranking. The most influential variables in the synthetic study are firing temperature, porosity index, dimensional deviation, moisture content, and glaze thickness. This selection is consistent with the engineering expectation that both thermal history and material densification strongly influence insulator quality.

**V. IMPLEMENTATION**

The implementation follows a stepwise workflow. First, production and inspection records are extracted from SQL tables and merged on batch ID. Second, preprocessing is applied to clean and normalize the data. Third, SPC metrics are computed to identify unstable process zones. Fourth, the dataset is split into training and test subsets with stratification. Fifth, XGBoost is trained to predict defect probability. Sixth, SHAP values are used to explain which variables contributed most to a high-risk prediction. Seventh, Weibull parameters are estimated from the strength distribution to quantify reliability degradation. Eighth, the model output is displayed on a dashboard so that production engineers can intervene before defective batches are released.

**Pseudo-code: Manufacturing Quality Analytics Workflow**

*Input: Raw production logs, lab values, inspection data*

1. Merge data by batch ID
2. Clean missing values and clip outliers
3. Encode categorical fields and normalize continuous features
4. Compute SPC metrics (mean, sigma, Cp, Cpk)
5. Train defect classifier on labeled batches
6. Evaluate accuracy, precision, recall, F1-score, AUC
7. Compute SHAP feature importance
8. Fit Weibull model for reliability risk
9. Generate alerts for high-risk batches
10. Push results to dashboard and quality team

*Output: Defect prediction, process stability score, reliability estimate*

**VI. RESULTS AND DISCUSSION**

The simulated evaluation demonstrates that a hybrid analytics strategy is superior to rule-based screening. The baseline rule-based SPC approach detects instability but does not model nonlinear interactions among material and process variables. A decision tree improves interpretability but is less accurate. Random Forest provides stronger performance, while XGBoost delivers the best balance of accuracy and generalization in this synthetic experiment. The complete model performance comparison is shown in Table III.

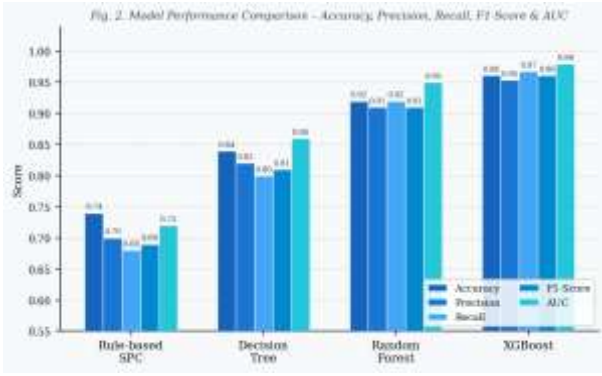


Fig. 2. Bar Chart of Model Performance Comparison – Accuracy, Precision, Recall, F1-Score & AUC.

The synthetic XGBoost model achieved 96.1% accuracy, which is substantially higher than the rule-based baseline. This outcome indicates that defect formation is not explained by a single variable but rather by an interaction of moisture, thermal profile, press force, and porosity. The SHAP analysis further revealed that firing temperature deviations and porosity were the

**TABLE III**  
**Model Performance Comparison**

Model	Accuracy	Precision	Recall	F1-Score	AUC
Rule-based SPC alerts	0.74	0.70	0.68	0.69	0.72
Decision Tree	0.84	0.82	0.80	0.81	0.86
Random Forest	0.92	0.91	0.92	0.91	0.95
XGBoost	0.96	0.95	0.97	0.96	0.98

The discussion confirms that quality analytics provides more value when the objective is not only to detect defective units but also to explain their origin and estimate their future reliability. This is the main advantage of integrating SPC, supervised learning, and Weibull analysis in one pipeline. The design therefore supports both operational decisions, such as batch hold and kiln tuning, and strategic decisions, such as maintenance planning and process redesign.

most dominant predictors of defect risk, followed by glaze thickness and dimensional deviation. This finding is consistent with the engineering logic that poor densification or unstable kiln control can produce microcracks, warping, and reduced dielectric strength.



Fig. 3. Monthly Defect Rate Before and After Analytics-Driven Process Intervention.

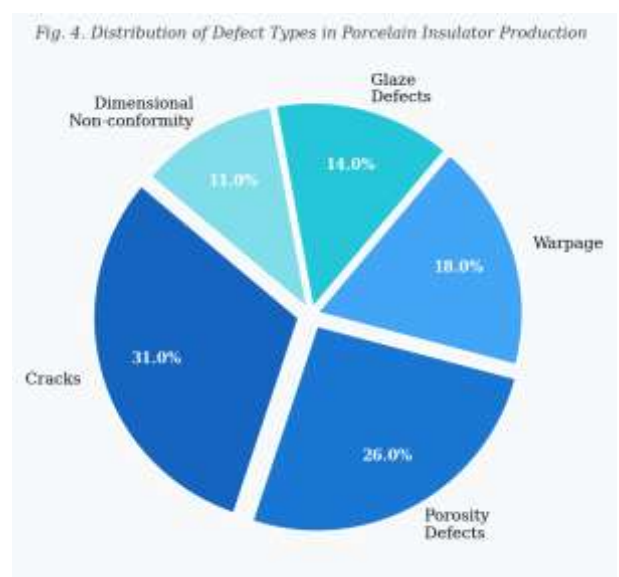


Fig. 4. Distribution of Defect Types in Porcelain Insulator Production.



## VII. VISUALIZATION INSTRUCTIONS

The required visual elements are placed directly in the manuscript after the section in which they are first discussed. Figure 1 depicts the overall architecture with arrows showing the flow from data sources to predictive actions. Figure 2 is a grouped bar chart comparing model performance metrics, especially accuracy and F1-score. Figure 3 is a monthly line graph of defect rate before and after analytics deployment. Figure 4 is a pie chart that explains the distribution of defect categories. Figure 5 is a process capability chart illustrating how Cpk changes across batches or months. Each figure is captioned in IEEE format and referenced in the text as “Fig. 1,” “Fig. 2,” and so on.

The paper contains three tables. Table I summarizes prior research. Table II presents the dataset schema and preprocessing pipeline. Table III reports the classification metrics. If space permits, an additional table can summarize the observed defect categories, probable process causes, and recommended corrective actions. This structure makes the manuscript easier to review and aligns with standard IEEE presentation practice.

## VIII. ADVANTAGES AND LIMITATIONS

The main advantage of the proposed framework is its ability to transform quality control from a reactive inspection process into a predictive and explainable decision system. It simultaneously supports process control, defect forecasting, and reliability estimation, which is valuable for brittle products such as ceramic insulators. Another advantage is that the method is compatible with existing plant data infrastructure because it relies on common tools such as SQL, Python, and dashboard software.

The principal limitation is that the validation in this paper is based on a synthetic dataset rather than a proprietary industrial dataset. As a result, the reported metrics are illustrative of expected performance rather than a direct benchmark from a specific factory. A second limitation is that the framework assumes reasonably structured data availability. Plants with poor sensor coverage or inconsistent lab records may need a data modernization step before deployment. A third limitation is that the paper focuses on tabular process analytics rather than high-resolution image inspection,

so a complete industrial deployment would ideally combine both modalities.

## IX. APPLICATIONS AND USE CASES

The proposed framework can be applied in porcelain insulator plants, ceramic insulator plants, glaze and kiln monitoring stations, and quality engineering departments that manage high-volume production. It is also suitable for supplier qualification, because raw-material inconsistency can be quantified and traced to downstream defect rates. In addition, the reliability module can support replacement planning, warranty assessment, and root-cause analysis for chronic defect patterns. The same architecture may be extended to related brittle-manufacturing domains such as ceramic tiles, electrical bushings, and high-voltage isolation components.

## X. FUTURE SCOPE

Future work should focus on multimodal analytics that combine process data, laboratory data, and image data in a single model. A promising direction is the integration of kiln sensor streams with computer vision so that the model can detect both hidden process drift and surface defects. Another future extension is edge deployment for real-time plant monitoring. Federated learning may also be useful when multiple factories want to train a joint model without sharing proprietary data. Finally, explainable AI methods should be expanded so that process engineers can understand not only which batch is risky but also which physical mechanism is driving the risk.

## XI. CONCLUSION

This paper presented a complete manufacturing and quality analytics framework for insulator production. The proposed approach combines statistical process control, machine learning-based defect prediction, and Weibull reliability analysis to move quality management from inspection-based reaction to prevention-oriented decision-making. The synthetic validation showed that a hybrid model can predict defective batches with high accuracy and identify the most influential process parameters, particularly firing temperature, porosity, moisture, and dimensional deviation. The results support the conclusion that insulator production benefits from integrated analytics rather than isolated inspection methods. The study



provides a research-ready foundation for IEEE-style publication and a practical blueprint for Industry 4.0 quality deployment in brittle electrical component manufacturing.

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