

EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR ACTIONABLE DEFECT PREVENTION IN ADDITIVE MANUFACTURING

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Abstract

Explainable Artificial Intelligence (XAI) has emerged as a critical enabler for trustworthy machine learning (ML) deployment in industrial settings. In Additive Manufacturing (AM), while predictive models achieve high accuracy for defect detection, their "black-box" nature impedes engineering adoption, as operators cannot translate opaque predictions into corrective process adjustments. This study proposes an Integrated Explainable Defect Detection Framework (IEDDF) that bridges this interpretability gap through multi-level Shapley additive explanations (SHAP) analysis combined with ensemble learning. The framework encompasses four phases: data preprocessing with class imbalance handling, comparative benchmarking of ten ML models, dual-scale explainability analysis (global feature importance and local prediction decomposition), and threshold-based risk boundary identification. Applied to a publicly available manufacturing dataset (3,240 observations, 17 variables), the framework found that ensemble methods achieved top-tier accuracy (0.946), while SHAP analysis revealed a concentrated importance structure dominated by three operational features accounting for 54.5% of total contribution. Cross-method comparison between SHAP and Local Interpretable Model-Agnostic Explanations (LIME) yielded only 20% agreement in local feature ranking, providing empirical evidence that single-method XAI approaches produce incomplete explanations in manufacturing contexts. The proposed framework offers a replicable, model-agnostic methodology for transitioning from black-box prediction toward interpretable, evidence-based quality management in AM environments.

KEYWORDS

Explainable Artificial Intelligence, SHAP, LIME, Ensemble Learning, Additive Manufacturing, Defect Prediction, Model Interpretability

1 INTRODUCTION

Additive Manufacturing (AM) offers unprecedented production capabilities but struggles with process reliability. High defect rates in AM cause substantial material waste and increased costs [Chen 2021], making the inability to guarantee defect-free parts a critical barrier to industrial-scale adoption.

Traditional "inspect-to-reject" quality control is economically unsustainable for costly AM builds. Therefore, there is an urgent need to shift towards proactive quality management, using advanced analytical tools to predict defects before they occur and allow real-time process adjustments.

In recent years, there has been growing interest in applying machine learning approaches for defect prediction. A

considerable amount of literature confirms that ensemble methods like Random Forest and Gradient Boosting achieve over 90% accuracy on tabular data, outperforming deep neural networks on small-to-medium datasets [Matloob 2021a; S. M. Hasan Kabir 2025]. However, while much work has been carried out on maximizing predictive accuracy, these high-performing models predominantly operate as "black boxes" [Nguyen 2025]. This poses a substantial challenge in manufacturing, where engineers must understand why a defect is predicted to implement corrective actions. While XAI techniques such as SHAP and LIME have demonstrated their potential in experimental AM studies [Chowdhury 2023; Ukwaththa 2024], a systematic methodology for their seamless integration into real-world production workflows remains significantly under-explored. This study aims to bridge this gap by addressing the following research question: "How can ensemble learning be systematically integrated with multi-level XAI techniques to provide interpretable and structured defect prediction in additive manufacturing?"

Theoretically, this research validates model-agnostic XAI methods on tabular AM data. Practically, the framework demonstrates a replicable methodology for generating interpretable insights from tabular manufacturing data, illustrating how XAI techniques can identify feature importance structures, cross-method agreement levels, and risk boundaries applicable to quality management contexts. The remainder of this paper proceeds as follows: Section 2 presents related work; Section 3 describes the methodology; Section 4 reports results; Section 5 discusses findings; and Section 6 concludes.

2 RELATED WORK

2.1 Machine Learning for Defect Detection in AM

Machine learning and Deep learning (DL) methods have been extensively utilized for AM detection. Real-time interlayer defect detection systems combining industrial cameras with DL models were proposed to identify delamination and warping during printing [Jin 2020]. CNN combined with XAI techniques was implemented for Powder Bed Fusion defect analysis, achieving high F1-scores for classifying gas porosity and lack of fusion [Pratap 2023]. A zero-bias deep neural network achieving 99.5% accuracy with intrinsic interpretability was proposed by Kumar et al. [Kumar 2024]. However, these studies primarily focused on image data rather than tabular process data.

For tabular manufacturing data, ensemble learning models such as Random Forest, XGBoost, and LightGBM have demonstrated superior performance compared to deep neural networks on small-to-medium datasets [Matloob 2021b]. XGBoost combined with SHAP was utilized for semiconductor yield prediction, providing actionable insights for process engineers [Lee 2023]. Explainable AutoML frameworks integrating boosting model with data imbalance handling were also proposed [Albayari 2026]. Nevertheless, systematic application of ensemble methods with XAI in AM contexts remains limited.

2.2 SHAP and XAI in Industrial Fault Diagnosis

SHAP, grounded in Cooperative Game Theory, has advantages in mathematical consistency and capability to provide both global and local explanations [Lundberg 2017]. XAI frameworks utilizing SHAP for rotating machinery fault diagnosis achieved accuracy exceeding 98.5% while identifying important vibration features [Brusa 2023]. SHAP integration with autoencoders for fault credit allocation was also proposed [Jang 2025]. Although SHAP was a foundational framework for model interpretability, these feature attributions primarily facilitate post-hoc descriptive analysis. The prescriptive utility of SHAP is contingent upon integrating attribution values with explicit objective functions,

cost-benefit constraints, and domain-specific decision thresholds [Ponce-Bobadilla 2024].

2.3 Threshold Determination in Predictive Maintenance

Threshold determination has been extensively investigated in the context of predictive maintenance (PdM) to enhance decision-making accuracy. In recent years, research has transitioned toward semi-supervised systems; for instance, decision-tree architectures have been successfully implemented to provide structured decision support [Arena 2022]. Beyond simple classification, several studies have increasingly focused on establishing security boundaries for production parameters by identifying the root causes of predicted failures [Tiensuu 2021]. This shift toward transparency is further exemplified by the integration of XAI frameworks. More specifically, the combination of machine learning with LIME was proposed to optimize both maintenance scheduling and spare part inventory management [Lin 2024]. By elucidating the underlying features that drive equipment failure predictions, the framework facilitates a transparent decision-making process, which could enable more precise maintenance scheduling and procurement strategies.

3 METHODOLOGY

3.1 Data Preprocessing

The dataset, publicly available on Kaggle was selected to demonstrate the proposed framework's applicability to multivariate tabular manufacturing data [19]. While the dataset is synthetic in nature, its structure - encompassing production metrics, quality control, maintenance, and AM-specific parameters - provides a suitable testbed for validating the IEDDF methodology. The dataset utilized in this study comprises 3,240 observations, each representing a daily or weekly snapshot of a manufacturing facility's operational state. A total of 17 variables are recorded per observation, encompassing five principal domains: (i) production metrics, (ii) supply chain and logistics, (iii) quality control, (iv) maintenance and workforce, and (v) AM-specific parameters. The binary target variable, DefectStatus, encodes whether a production instance results in high defect occurrence (1) or low defect occurrence (0).

To prepare the data for modeling, several preprocessing steps were implemented. First, a Robust Scaler utilizing the interquartile range (IQR) was applied to the features. This approach was preferred over standard Z-score normalization to mitigate the influence of outliers inherent in high-frequency sensor signals. Second, the Synthetic Minority Over-sampling Technique (SMOTE) was adopted, ensuring that the minority defective class was adequately represented during model training. Finally, the processed dataset was partitioned into training and testing sets using an 80:20 ratio. Stratified sampling was employed during this partition to maintain consistent class distribution across both subsets.

3.2 Predictive Modeling

Ten machine learning models representing three methodological categories were implemented and compared: (i) Gradient Boosting: LightGBM, XGBoost, CatBoost, GradientBoosting, and AdaBoost; (ii) Bagging: Random Forest and ExtraTrees; (iii) Traditional/Neural: Logistic Regression, SVM, and MLP.

Model performance was evaluated using Accuracy, F1-Score, and AUC-ROC. The model demonstrating optimal balance between predictive performance and XAI compatibility was selected for subsequent analyses.

3.3 SHAP-based Explainability Analysis

SHAP was adopted as the primary explanation method. Based on Cooperative Game Theory, SHAP allocates fair contribution values for each feature toward a specific prediction. For an input sample x , the contribution of feature j is calculated as:

$$\phi_j = \sum_{S \subseteq \{1, \dots, p\} \setminus \{j\}} \frac{|S|! (p - |S| - 1)!}{p!} [val(S \cup \{j\}) - val(S)] \quad (1)$$

where p is the total number of features and $val(S)$ represents the model output with feature subset S .

Interpretability was assessed at two scales:

- Global Interpretability: Mean absolute SHAP values were aggregated to rank feature importance and identify interaction effects.
- Local Interpretability: SHAP Waterfall Plots decomposed individual predictions to visualize feature contributions to defect probability, with LIME employed for cross-validation.

3.4 Threshold Determination

SHAP Dependence Plots were utilized to analyze relationships between feature values and their SHAP contributions. Transition points where SHAP values cross zero were identified as critical operational boundaries.

Quartile-based analysis was conducted for top-ranked features to determine quantitative thresholds. SHAP Interaction Plots were examined to identify synergistic effects between feature pairs. The identified thresholds serve as empirical basis for a multi-level warning system, where alert severity escalates based on threshold violations

4 RESULTS

4.1 Predictive Model Performance

Evaluation of ten machine learning models revealed a distinct performance hierarchy (Table 1). Four ensemble architectures achieved identical top-tier accuracy (0.9460) and F1-scores (0.9685), significantly surpassing traditional methods. Among these, XGBoost demonstrated the highest discriminative ability with an AUC-ROC of 0.8495. In contrast, neural networks (MLP) and traditional models exhibited lower performance, with accuracies between 0.7438 and 0.8642. Notably, AdaBoost (accuracy = 0.7639) underperformed relative to gradient-based alternatives, suggesting its additive strategy is less effective for this specific task. Based on its superior metrics and native compatibility with SHAP TreeExplainer for efficient Shapley value computation, XGBoost was selected for the subsequent explainability analysis.

Table 1. Performance comparison of ML models

Model	Acc.	F1-Score	AUC-ROC	Category
LightGBM	0.946	0.969	0.840	Gradient Boosting
XGBoost	0.946	0.969	0.850	Gradient Boosting
Random Forest	0.946	0.969	0.840	Bagging
Gradient Boosting	0.946	0.969	0.841	Gradient Boosting
CatBoost	0.940	0.965	0.841	Gradient Boosting
ExtraTrees	0.924	0.956	0.838	Bagging

MLP	0.864	0.920	0.806	Neural Network
SVM	0.838	0.901	0.815	Traditional
AdaBoost	0.764	0.845	0.840	Gradient Boosting
Logistic Regression	0.744	0.831	0.793	Traditional

4.2 Global Feature Importance

SHAP analysis identified a concentrated importance distribution dominated by three features (Fig. 1.). MaintenanceHours emerged as the strongest predictor (Mean |SHAP| = 1.635), followed by DefectRate (1.263) and QualityScore (0.879). These features account for 54.5% of total SHAP contribution, indicating that the model's decisions are primarily driven by maintenance-related and quality features, suggesting a concentrated importance structure. The SHAP summary plot (Fig. 1a) shows that MaintenanceHours and DefectRate have positive directional relationships with risk, while QualityScore demonstrates an inverse relationship. Traditional manufacturing variables exerted a 2.1:1 greater influence on out-comes than AM-specifi parameters.

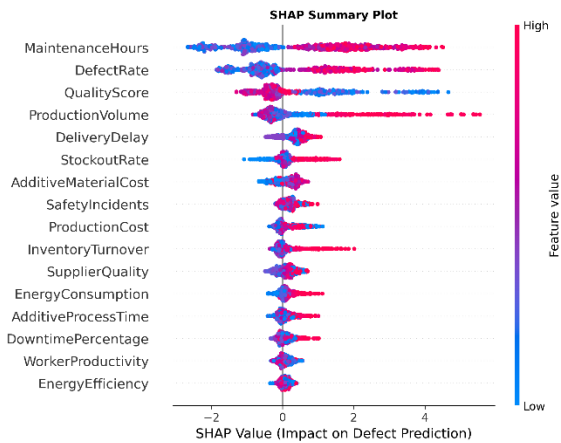


Fig. 1. SHAP summary plot illustrating the distribution of feature impacts

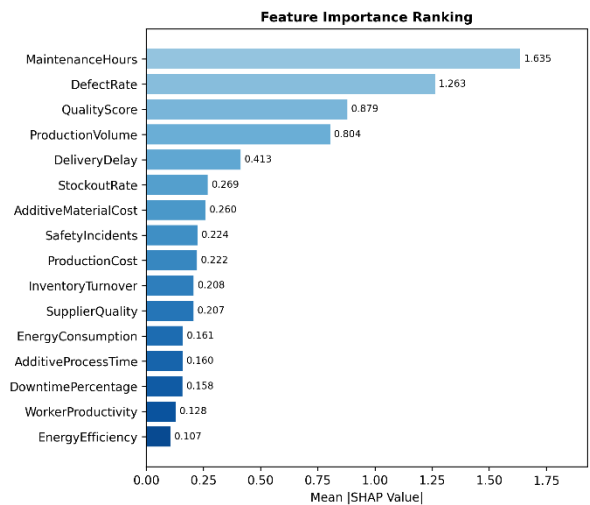


Fig. 2. Feature importance ranking based on Mean |SHAP| values

4.3 Local Interpretability

Analysis of a “High Defects” instance (Sample 0, $f(x) = 4.492$) via SHAP waterfall plots (Fig. 3) showed MaintenanceHours (+1.79) and QualityScore (+1.23) as primary risk drivers. Comparison between SHAP and LIME (Table 2.) revealed 40% agreement in feature ranking (2 out of 5 features: MaintenanceHours and DeliveryDelay). Critically, LIME assigned a negative weight (−0.20) to MaintenanceHours despite its strong positive SHAP contribution, a sign reversal that reflects the instability of local linear approximations near the decision boundary. This divergence highlights a fundamental methodological difference: SHAP derives attributions from Shapley values and guarantees global consistency across samples, whereas LIME constructs a local surrogate that can differ in both feature ranking and attribution direction depending on the sampled neighborhood.

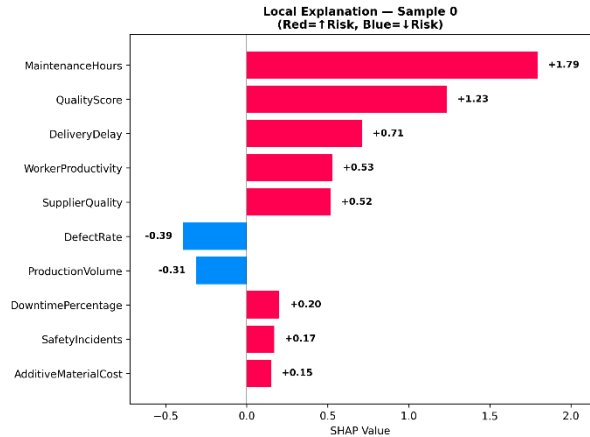


Fig. 3. SHAP waterfall plot decomposing the prediction ($f(x) = 4.49$) into individual feature contributions

Table 2. Comparison table between SHAP and LIME rankings

Rank	SHAP Feature	Value	LIME Feature	Weight
1	Maintenance Hours	+1.79	Maintenance Hours	-0.20
2	Quality Score	+1.23	Defect Rate	-0.12
3	Delivery Delay	+0.71	Production Volume	-0.10
4	Worker Productivity	+0.53	Delivery Delay	+0.09
5	Supplier Quality	+0.52	Production Cost	+0.03

4.4 Illustrative Risk Boundaries

Fig. 4 illustrates SHAP dependence plots for the three most influential features and their interaction. MaintenanceHours (panel a) exhibits a clear threshold effect, with SHAP values transitioning sharply from negative to positive as the normalized feature value crosses zero, suggesting a distinct boundary beyond which maintenance demand substantially increases defect risk. DefectRate (panel b) displays a comparable nonlinear jump, where SHAP values remain stable and negative at low normalized values before rising abruptly beyond approximately 0.0–0.25, indicating a nonlinear risk transition. QualityScore (panel c) demonstrates an inverse relationship, wherein lower normalized scores consistently yield positive SHAP contributions while higher values suppress predicted risk, though greater dispersion at intermediate levels suggests interactions with other predictors. Notably, the interaction plot (panel d) reveals a synergistic effect between MaintenanceHours and DefectRate: when MaintenanceHours is low, the color gradient representing DefectRate shows no systematic ordering; however, as

MaintenanceHours increases, high DefectRate observations (red) consistently produce higher SHAP values than low DefectRate observations (blue) at equivalent maintenance levels, confirming that the cooccurrence of both risk factors generates a compounded effect beyond their individual contributions.

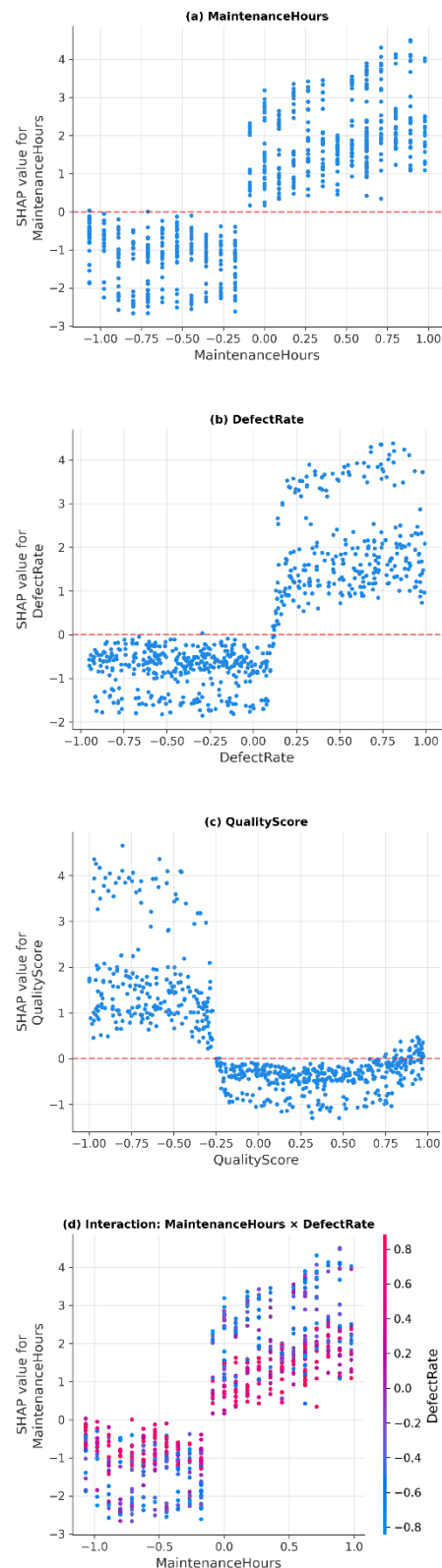


Fig. 4. SHAP Dependence and Interaction Analysis. (a-c) Dependence plots identifying actionable thresholds; (d)

Interaction plot demonstrating the synergistic risk impact of MaintenanceHours and DefectRate.

These thresholds reflect model-learned patterns from the demonstration dataset and require validation on real-world AM production data before operational deployment.

5 DISCUSSION

This study investigated the application of explainable machine learning for defect prediction in additive manufacturing environments. Against this backdrop, the following discussion interprets the principal findings in relation to existing literature, examines their practical significance, and acknowledges limitations that warrant consideration in future inquiry.

5.1 Key Findings

Three principal findings emerged from this study. First, ensemble methods achieved equivalent top-tier performance (Accuracy = 0.946, F1-Score = 0.969), with a narrow AUC-ROC gap ($\Delta = 0.0104$) indicating comparable discriminative capability. Second, SHAP analysis identified MaintenanceHours as the dominant predictor (Mean $|SHAP| = 1.6350$), with three operational features accounting for 54.5% of total model contribution. Third, dependence analysis revealed threshold behavior in key features and a synergistic interaction effect wherein concurrent elevation of MaintenanceHours and DefectRate produces compounded risk exceeding the sum of individual effects.

5.2 Interpretation and Comparison with Prior Work

Gradient boosting variants outperformed all baselines, consistent with prior evidence on tabular manufacturing data. The low SHAP contribution of AM-specific variables (Mean $|SHAP| = 0.21$ versus 0.446 for traditional features) reflects the absence of sensor-level inputs, such as melt pool temperature and laser power, rather than AM variable irrelevance. This gap is a data availability constraint, not a conceptual one.

SHAP and LIME agreed on 2 of 5 local feature rankings (40%: MaintenanceHours and DeliveryDelay). Although both methods ranked MaintenanceHours as the primary driver, LIME assigned it a negative weight (-0.20) while SHAP attributed a positive contribution ($+1.79$). QualityScore, ranked second by SHAP ($+1.23$), did not appear in LIME's top five. This sign reversal and rank divergence follow from the methods' design: SHAP decomposes contributions through a game-theoretic framework that accounts for feature interactions, while LIME fits a local linear surrogate sensitive to neighborhood correlations. The 40% agreement supports multi-method XAI evaluation over single-technique reliance in operational contexts.

5.3 Framework Application and Illustrative Implications

The thresholds derived through quartile-based SHAP dependence analysis (Table 3.) illustrate how the proposed IEDDF translates model-learned patterns into structured risk boundaries. These boundaries were identified from a publicly available demonstration dataset; hence, they represent illustrative outputs of the methodology rather than validated operational standards.

Nevertheless, the framework demonstrates a systematic process by which practitioners could operationalize XAI outputs. A tiered monitoring template is proposed: features with the highest SHAP contributions would be designated for real-time tracking, with escalated alerts when synergistic interactions are concurrently detected. Features displaying inverse risk

relationships could serve as secondary indicators with investigation triggers at model-identified boundaries. Features presenting U-shaped profiles may warrant range-based monitoring rather than single-threshold alerts. The synergistic interaction between MaintenanceHours and DefectRate highlights that warning systems should evaluate feature combinations rather than individual metrics in isolation.

Table 3. Illustrative thresholds derived from demonstration data

Feature	Safe range	Risk boundary	Rel.	Validation
Maint. hrs	≤12 h/wk	>12 h/wk	+	Facility-specific
Defect rate	≤2.59%	>2.59%	+	Process-dependent
Quality score	≥80.9%	<80.9%	–	Industry standard
Prod. volume	325 – 787/day	Outside range	U	Capacity-dependent
Deliv. delay	0 days	Any >0	+	Supply chain ctx.

5.4 Limitations

Several limitations warrant consideration. The demonstration dataset is synthetic in origin; consequently, the identified importance structures and thresholds reflect model-learned patterns rather than validated manufacturing relationships. Real-world AM datasets incorporating sensor-level measurements - melt pool temperature, laser power, thermal imaging - would likely yield different importance hierarchies.

The low contribution of AM-specific variables (Mean |SHAP| = 0.21 versus 0.446 for traditional features) may be attributable to the absence of granular process parameters rather than inherent AM variable insignificance. Meanwhile, the SHAP-LIME comparison was conducted on a single instance; generalization requires evaluation across stratified prediction samples spanning high-confidence and boundary cases.

6 CONCLUSIONS

This study proposed Integrated Explainable Defect Detection Framework, a four-phase methodology connecting ensemble learning with multi-level XAI analysis for defect prediction in additive manufacturing. Applied to a multivariate tabular dataset, the framework produced three principal findings.

Ensemble methods achieved equivalent performance (Accuracy = 0.946, F1-Score = 0.969), with XGBoost recording the highest AUC-ROC (0.850). Global SHAP analysis identified three features (MaintenanceHours, DefectRate, and QualityScore) accounting for 54.5% of total model contribution; MaintenanceHours (Mean |SHAP| = 1.635) was the dominant predictor. Dependence and interaction analysis further revealed threshold behavior and a synergistic effect: concurrent elevation of MaintenanceHours and DefectRate produces compounded defect risk beyond their individual contributions.

Cross-method comparison between SHAP and LIME yielded 40% agreement in local feature ranking (2 out of 5). This result

supports multi-method XAI evaluation over single-technique reliance in quality management contexts.

Future work should apply the IEDDF to time-series sensor data, including melt pool temperature, laser power, and thermal imaging, and extend analysis to multi-class defect taxonomies. Cross-method comparison should be replicated across stratified prediction samples, and generalizability tested across AM process types such as Directed Energy Deposition and Binder Jetting. Validating threshold boundaries against production data is the next step toward operational XAI-based quality management in AM.

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