

An XGBoost-Driven Intelligent Classification Model for Textile Product Quality Eligibility: A Case Study at PT ABC Textile

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Abstract - Product quality is a critical aspect of the textile industry because it determines whether a product meets the company's quality standards. This study develops a product eligibility classification model using the XGBoost algorithm to support the Quality Control (QC) process at PT ABC Textile. The novelty of this research lies in positioning XGBoost as an interpretability-driven decision-support tool by integrating real QC inspection data, feature importance and SHAP-based interpretability analysis, and stratified 5-fold cross-validation to support practical QC decision-making. The dataset consists of 500 samples manually labeled based on the company's quality criteria and includes four technical features: Yarn Strength, Knitting Density, Color, and Defect Level. Data preprocessing involved data cleaning, label transformation, and MinMaxScaler normalization. Model performance was evaluated using stratified 5-fold cross-validation to ensure robust and unbiased assessment. The experimental results demonstrate stable and high classification performance across all folds, with strong class-wise precision, recall, and F1-score values. Confusion matrix analysis indicates that the model performs particularly well in identifying Non-Eligible products, which is critical for minimizing quality risks in industrial applications. Overall, the proposed approach demonstrates that XGBoost can effectively support textile quality control as an interpretable and reliable decision-support system. Future work may explore dataset expansion and cost-sensitive learning to further enhance industrial applicability.

Keywords – XGBoost; Classification; Textile Products, Quality Control, Data Mining

1. INTRODUCTION

Product eligibility is a fundamental aspect of the textile industry because it determines whether a product meets the required quality standards before being marketed [1]. Ineligible textile products not only lead to direct financial losses but may also damage a company's reputation, reduce consumer trust, and weaken competitiveness in the textile market. Therefore, textile manufacturers, including PT ABC Textile, continuously strive to improve their quality control (QC) systems to minimize defective products and increase the proportion of eligible outputs [2]. However, ensuring product eligibility is a complex task due to the involvement of multiple interacting factors. Textile quality is influenced by various technical parameters such as yarn tensile strength, knitting density, color consistency, defect level, production process variability, and raw material characteristics. The interaction of these factors can result in product ineligibility, increased rework costs, material waste, and reduced production efficiency if not properly managed [3]. To mitigate these issues, periodic and systematic product quality evaluation is required before the finishing or distribution stages. Conventional QC practices rely heavily on manual inspection by operators, which is time-consuming, subjective, and prone to human error. In this context, machine-learning-based approaches offer a promising alternative by enabling data-driven, consistent, and scalable product eligibility prediction to support industrial QC decision-making.

In machine learning [4], classification techniques are widely used for industrial quality assessment, allowing products to be categorized into classes such as “Eligible,” “Needs

Improvement,” or “Not Eligible” based on measurable production features. Classification results can support operational decisions, including production parameter adjustment, machine calibration, and raw material quality control, thereby improving overall manufacturing efficiency. Among various classification algorithms, XGBoost (Extreme Gradient Boosting) has gained considerable attention due to its high predictive accuracy, robustness to noise, and ability to handle structured numerical data commonly found in industrial environments [5]. XGBoost employs a boosting-based ensemble of decision trees with regularization mechanisms that reduce overfitting and improve generalization compared to traditional methods such as Decision Tree or Naïve Bayes.

Previous studies have demonstrated the effectiveness of machine learning [1] for textile quality analysis. The work in [5] reported that ensemble-based models, including XGBoost, improved fabric quality prediction and reduced defect rates in textile manufacturing. Meanwhile, studies in [3] and [4] explored machine learning approaches such as CNN and SVM for automated defect detection and early-stage quality prediction, showing improvements in inspection efficiency and defect prevention. Research in [6] further applied data mining techniques such as Decision Tree, Naïve Bayes, SVM, and K-Means to classify and cluster textile defects based on texture, color, and machine parameters. Despite these advances, several limitations remain. First, many existing studies focus primarily on performance comparison based on accuracy metrics, with limited attention to model interpretability and feature-level analysis that are crucial for industrial decision-making. Second, research applying XGBoost to textile product eligibility classification using real production data from local manufacturing companies remains limited. Moreover, issues such as class imbalance and robust evaluation using stratified k-fold cross-validation are often insufficiently addressed.

Therefore, this study aims to bridge these gaps by developing an XGBoost-based product eligibility classification model using real QC inspection data from PT ABC Textile. The contribution of this research lies not in proposing a new algorithm, but in positioning XGBoost as an interpretability-driven decision-support tool for industrial quality control. This study integrates stratified 5-fold cross-validation to ensure robust performance evaluation, explicitly considers class imbalance in eligibility classes, and employs feature importance and SHAP-based analysis to provide analytical insights into the contribution of each production feature. By utilizing real production features—Yarn Strength, Knitting Density, Color, and Defect Level—this research provides both predictive performance and explainable insights that can support QC personnel in understanding the causes of product ineligibility. The results are expected to offer practical industrial implications, including improved defect prevention, reduced rework costs, and enhanced reliability of QC decision-making in textile manufacturing.

2. RESEARCH METHOD

This research follows a structured and systematic workflow to ensure methodological rigor and reproducibility. The proposed framework consists of five main stages: data collection, data preprocessing, data classification, hyperparameter tuning, and data interpretation. The overall workflow of the research is illustrated in Figure 1. The core classification method employed in this study is the Extreme Gradient Boosting (XGBoost) algorithm.

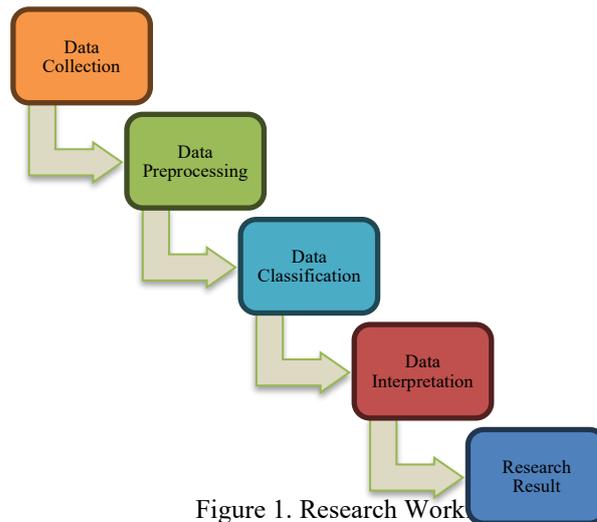


Figure 1. Research Work

2.1 Data Collection

This stage serves as the initial step of the research process. Data collection is the procedure of obtaining relevant and accurate information to support analysis and research decision-making [7]. The collected data consist of several textile testing parameters that serve as product eligibility standards, including Real Yarn Strength, Real Knitting Density, Real Color, and Real Defect Level. These data represent the results of quality measurements conducted during the textile production inspection process. A total of 500 QC inspection records were successfully obtained. The dataset was gathered from a specific production period and remained in its raw form, requiring cleaning procedures before being used for analysis and modeling.

2.2 Data Preprocessing

Data preprocessing is a critical stage aimed at cleaning, preparing, and optimizing data to ensure reliable and accurate machine learning modeling [8]. Given that QC inspection data often contain missing values and inconsistent measurement formats, preprocessing is essential to improve data quality and model robustness. The preprocessing stages conducted in this study are described as follows.

1. Data Cleaning

Data cleaning involves removing noise and inconsistencies that may negatively affect model performance [9]. In this stage, irrelevant attributes were removed, missing values were handled, duplicate records were eliminated, and numerical measurement units were standardized. Additionally, outliers that fell outside the predefined QC standard thresholds were examined and corrected where appropriate. These steps ensured that the final dataset of 500 records was suitable for classification modeling.

2. Data Labelling

After data cleaning, each record was assigned a product eligibility label based on the QC standards applied at PT ABC Textile. The dataset was categorized into three classes: Eligible, Requires Improvement, and Not Eligible. This labeling process serves as the ground truth reference for supervised learning and subsequent model evaluation.

3. Data Normalization

Data normalization was applied to ensure that all features shared a comparable value scale, which is important for improving learning stability and convergence [7][10]. Since the feature values varied across different numerical ranges, Min–Max normalization was employed to scale each feature into the range [0, 1], as defined by:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Description :

X = the original value of a feature
 min = the minimum value of the feature
 max = the maximum value of the feature

$$X_{scaled} = \text{normalized value (Min – Max scaled value)}$$

where X denotes the original feature value, X_{min} and X_{max} represent the minimum and maximum values of the feature, respectively, and X_{scaled} is the normalized value.

2.3 Data Classification

Classification is a machine learning technique used to assign data instances into predefined classes based on their attributes [9], [11]–[14]. In this study, product eligibility classification was performed using the XGBoost algorithm. XGBoost is a gradient boosting ensemble method that constructs multiple decision trees sequentially, where each tree attempts to correct the errors made by the previous trees.

The model uses four input features—Yarn Strength, Knitting Density, Color, and Defect Level—to predict three output classes: Eligible, Requires Improvement, and Not Eligible. To ensure robust and unbiased performance evaluation, stratified 5-fold cross-validation was employed. This approach preserves the class distribution in each fold and mitigates the effects of class imbalance in the dataset.

The XGBoost objective function can be expressed as:

$$L^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (2)$$

Description :

$L(t)$ = Loss function

n = Number of model iterations

y_i = Actual target value

$\hat{y}_i^{(t-1)}$ = Cumulative prediction up to iteration t-1

$f_t(x_i)$ = Additional function at the t-th iteration

$\Omega(f_t)$ = Regularization function measuring model complexity

2.4 Hyperparameter Tuning

Hyperparameter tuning aims to identify the optimal combination of model parameters that maximize predictive performance and generalization ability [15]. Since hyperparameters cannot be learned directly from the data, they must be specified prior to model training. In this study, hyperparameter optimization was conducted using Grid Search combined with stratified cross-validation.

Key XGBoost hyperparameters tuned in this study include learning_rate, n_estimators, max_depth, subsample, and colsample_bytree [16]. These parameters control the learning speed, tree complexity, sampling strategy, and feature utilization of the model. Proper hyperparameter tuning is essential to balance bias and variance and to achieve stable performance across different validation folds.

2.5 Data Interpretation and Model Evaluation

The final stage of this research focuses on interpreting and evaluating the classification results. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score [11]. These metrics provide a comprehensive assessment of classification effectiveness, particularly in multi-class and imbalanced data scenarios.

Accuracy is defined as:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (3)$$

Description :

TP = True Positif

TN = True Negatif

FP = False Positif

FN = False Negatif

Precision, recall, and F1-score are calculated as follows:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1 - Score = 2x \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

In addition to quantitative metrics, a confusion matrix was used to analyze classification errors across eligibility classes. Furthermore, feature importance and SHAP-based analysis were employed to provide interpretability insights, allowing QC personnel to understand how each production feature contributes to product eligibility decisions. This interpretability aspect strengthens the applicability of the proposed model as a decision-support tool in industrial quality control.

3. RESULT AND DISCUSSION

3.1 Data Collection

The dataset used in this study was obtained from the Quality Control (QC) department of PT ABC Textile and consists of secondary data in the form of documented textile inspection records. A total of 500 textile product samples were collected, each described by four technical quality attributes: Yarn Strength, Knitting Density, Color, and Defect Level. Each product was labeled into one of three eligibility classes: Eligible, Requires Improvement, and Not Eligible.

An analysis of class distribution reveals an imbalanced dataset, with 267 samples labeled as Eligible, 190 samples as Requires Improvement, and 43 samples as Not Eligible. This imbalance reflects real industrial conditions, where severely defective products occur less frequently but are critical for quality assurance. Therefore, special attention was given to evaluation strategies that mitigate bias toward majority classes.

Table 1. Research Dataset Table

ID	Real Knitting	Density	Real Color	Real Defect	Level Eligibility
24	49,65	129,31	2,24	1,42	Requires Improvement
25	42,57	143,21	2,07	1,15	Eligible
26	34,12	121,83	0,69	5,58	Not Eligible
27	36,37	123,33	1,87	1,33	Not Eligible
28	36,84	132,92	1,18	5,19	Not Eligible
29	30,95	124,67	0,76	2,53	Not Eligible
30	48,92	123,11	1,86	1,5	Requires Improvement

31	49,3	141,41	2,35	3,08	Eligible
32	39,51	139,28	1,37	2,58	Requires Improvement
33	46,92	141,29	1,92	3,79	Requires Improvement
34	32,94	123,93	1,4	5	Not Eligible
35	39,46	131,61	0,67	5,03	Not Eligible

3.2 Class Distribution of Eligibility and Feature Correlation Analysis

This subsection presents an exploratory analysis of the dataset characteristics, including class distribution and feature–label correlation, prior to the preprocessing and modeling stages. This analysis is essential to understand the inherent structure of the data and to justify the selection of evaluation strategies and performance metrics.

3.2.1 Class Distribution of Eligibility

Based on the collected Quality Control (QC) data from PT ABC Textile, the distribution of product eligibility classes is summarized as follows:

```
Distribusi kelas:
Eligibility
0      267
1      190
2       43
```

Figure 2. Class Distribution of Eligibility

The distribution indicates that the dataset is imbalanced, with the Not Eligible class dominating the samples and the Eligible class representing a relatively small proportion of the data. This imbalance reflects real-world industrial conditions, where products that fully meet quality standards are generally fewer than those requiring improvement or rejection.

To address this condition and avoid biased performance evaluation, this study employed stratified 5-fold cross-validation, which preserves the original class distribution in each fold. Furthermore, the F1-score was selected as the primary evaluation metric, as it provides a balanced measure of precision and recall and is more suitable than accuracy alone for imbalanced multi-class classification problems.

3.2.2 Feature–Label Correlation Analysis

To examine the relationship between input features and the eligibility label, Pearson correlation analysis was conducted. The correlation coefficients between each feature and the eligibility label are presented as follows:

```
Korelasi fitur vs label:
Label          1.000000
Yarn Strength  0.516968
Knitting Density 0.483439
Color          0.219926
Defect Level   -0.449173
Name: Label, dtype: float64
```

Figure 3. Feature–Label Correlation Analysis

The results indicate that Yarn Strength has the strongest positive correlation with product eligibility, suggesting that higher yarn strength significantly increases the likelihood of a product being classified as Eligible. Knitting Density also exhibits a strong positive correlation, highlighting its importance in determining textile quality.

In contrast, Defect Level shows a moderate negative correlation, indicating that an increase in defect intensity substantially reduces product eligibility. Meanwhile, Color demonstrates a weaker positive correlation, implying that although color consistency contributes to eligibility determination, its influence is less dominant compared to

physical and structural quality attributes. These findings support the selection of the four features used in this study and are consistent with the results of the XGBoost feature importance and SHAP analyses presented in the subsequent sections. Together, they confirm that the chosen features are both statistically relevant and practically meaningful for textile product eligibility classification.

3.3 Data Preprocessing

Data preprocessing was performed to ensure data quality and modeling reliability [17][7]. The preprocessing steps included data cleaning, labeling, and normalization. Irrelevant attributes were removed, missing values were handled, duplicate records were eliminated, and measurement scales were standardized.

Each product record was labeled according to PT ABC Textile’s QC standards. Products that fully met quality requirements were classified as Eligible, those close to acceptable thresholds were classified as Requires Improvement, and products failing to meet minimum standards were classified as Not Eligible. This labeling process provided a reliable ground truth for supervised learning. To ensure consistent feature scaling, Min–Max normalization was applied to all numerical attributes, transforming feature values into the range [0, 1]. This step improved model stability and convergence during training.

1. Data Cleaning

The initial stage of data preprocessing involved removing unnecessary columns from the dataset. This process was carried out manually using Microsoft Excel. In this study, only features that have a direct influence on the eligibility of textile products were utilized. The classification process was based on four main features, namely Yarn Strength, Knitting Density, Color, and Defect Level. The selection of these features was determined according to the company’s inspection standards and their relevance in classifying products as Eligible, Requiring Improvement, or Not Eligible. Consequently, the data cleaning process resulted in a more concise, consistent, and well-structured dataset that is ready for further processing in the labeling and normalization stages.

2. Data Labelling

In the data labeling stage, each product was classified into one of three eligibility categories based on its technical quality parameters, namely Real Yarn Strength, Real Knitting Density, Real Color, and Real Defect Level. Products that met the required quality standards were categorized as Eligible. Items in this category exhibit adequate yarn strength, compliant knitting density, and low defect levels, as shown in the records with IDs 25 and 31. Products whose parameter values were close to the acceptable thresholds but still required adjustments were categorized as Requires Improvement. Items in this category typically display moderate deviations in one or more technical attributes, indicating that their quality can still be enhanced through minor corrective actions. Examples include IDs 24, 30, 32, and 33. Meanwhile, products that failed to meet the minimum quality requirements—such as those with low yarn strength, inadequate knitting density, notable color deviations, or high defect levels—were categorized as Not Eligible. Products in this category fall significantly below the established quality standards and are unsuitable for distribution without substantial corrective measures. This group includes the items with IDs 26, 27, 28, 29, 34, and 35.

3. Data Normalization

The final stage of the preprocessing procedure was conducted by applying normalization to the dataset. After the data were cleaned and assigned labels according to their eligibility categories, the next step involved performing normalization to standardize the value ranges of each numerical feature. This normalization process was carried out using the MinMaxScaler method from the Scikit-Learn library with the following configuration.

```
scaler = MinMaxScaler()
X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

Figure 4. Data Normalization Process Using Min-Max Scaling

Before applying normalization, the dataset was first divided into training and testing sets using the train-test split function. The data were split using an 80% : 20% ratio, resulting in 400 training samples and 100 testing samples from a total of 500 entries. This split was intended to provide an adequate proportion of data for model training while ensuring a sufficient amount for evaluating model performance with the following configuration.

```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, stratify=y, random_state=42)
```

Figure 5. Data Splitting into Training and Testing Sets

Below is the dataset display after completing the entire preprocessing sequence, which includes data cleaning, label assignment, and normalization.

3.4 Model Training Using XGBoost

The next step is to perform modeling using the XGBoost algorithm

```
final_model = xgb.XGBClassifier(**best_params,
    objective="multi:softmax",
    num_class=len(np.unique(y)),
    eval_metric="mlogloss",
    random_state=42)

final_model.fit(X_train,y_train,sample_weight=sw_train)
```

Figure 6. Model Training Using XGBoost

The final classification model was developed using the Extreme Gradient Boosting (XGBoost) algorithm with the optimal hyperparameters obtained from the tuning process. The model was configured for multiclass classification using the softmax objective function. The number of output classes was automatically adjusted based on the target labels, and the multiclass logarithmic loss was employed as the evaluation metric. To address class imbalance, sample weights were applied during the training phase. This approach ensures that the model learns more effectively from minority classes and improves overall classification performance. The trained XGBoost model was then used for subsequent testing and evaluation.

3.5 Data Interpretation

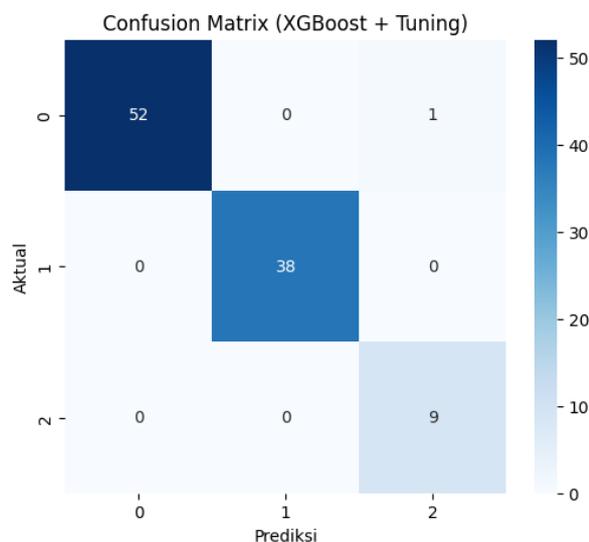


Figure 7. Confusion Matrix of the Testing Model

Based on the experimental results obtained, Figure 6 illustrates the performance of the testing model through the confusion matrix generated by the tuned XGBoost algorithm. The confusion matrix presents the distribution of prediction results across three classification categories: Eligible, Requires Improvement, and Not Eligible.

For the Eligible category, the model correctly classified 52 instances, with only 1 instance misclassified as Not Eligible, and no instances incorrectly predicted as Requires Improvement. This indicates a very strong ability of the model to identify Eligible products accurately. In the Requires Improvement category, the model achieved 38 correct classifications, with no misclassifications into either of the other categories, demonstrating perfect performance for this class. Meanwhile, for the Not Eligible category, the model correctly classified 9 instances, with no misclassification into other categories. Overall, these results demonstrate that the tuned XGBoost model performs with a very high level of accuracy on the testing dataset. The model shows excellent classification capability across all categories, particularly in distinguishing Requires Improvement and Not Eligible products without error. The minimal misclassification observed in the Eligible category suggests that the model operates reliably and effectively in classifying product eligibility based on the predefined labels.

3.6 XGBoost Model Evaluation Using Stratified 5-Fold Cross-Validation

To address class imbalance and ensure a robust performance evaluation, this study employed stratified 5-fold cross-validation. This validation strategy maintains the original class distribution within each fold and provides a more reliable estimation of the model's generalization ability compared to a single train-test split.

The XGBoost model was evaluated using the F1-score as the primary performance metric, as it effectively balances precision and recall and is well-suited for imbalanced multi-class classification problems. The F1-score results obtained for each fold are summarized as follows:

```
Fold 1 F1: 1.0
Fold 2 F1: 0.9547131445170661
Fold 3 F1: 0.9717168796116163
Fold 4 F1: 1.0
Fold 5 F1: 1.0

Mean F1: 0.9852860048257366
Std F1 : 0.018805987921375958
```

Figure 8. Model Evaluation Using Stratified 5-Fold Cross-Validation

Based on these results, the model achieved a mean F1-score of 0.985 with a standard deviation of 0.019, indicating high stability and consistency across different data partitions. The low variance among folds demonstrates that the model's performance is not dependent on a specific data split and confirms its strong generalization capability when applied to unseen data.

3.7 Classification Performance Analysis

Further evaluation was conducted using precision, recall, and F1-score for each eligibility class. The model achieved an overall accuracy of 0.99, with weighted precision, recall, and F1-score values all exceeding 0.99. Notably, the model demonstrated excellent performance in identifying Not Eligible products, achieving perfect recall for this class.

```
=== Classification Report ===
              precision    recall  f1-score   support

     0           1.00        0.98        0.99         53
     1           1.00        1.00        1.00         38
     2           0.90        1.00        0.95          9  iSN : 1412-2693, DOI :

 accuracy          0.99          0.99          0.99         100
 macro avg         0.97          0.99          0.98         100
 weighted avg      0.99          0.99          0.99         100
```

Figure 9. Classification Performance Analysis

This result is particularly important from an industrial perspective, as misclassifying defective products as eligible can lead to significant quality risks, customer dissatisfaction, and financial losses. The high recall for the Not Eligible class indicates that the model is effective in minimizing such risks.

3.8 Feature Importance and Interpretability Analysis

To enhance model interpretability, feature importance analysis was conducted using the XGBoost model. The results show that Yarn Strength, Defect Level, and Knitting Density are the most influential factors in determining product eligibility, with importance scores of approximately 0.30, 0.29, and 0.28, respectively. Color exhibited the lowest importance score, indicating a relatively smaller contribution compared to the other features.

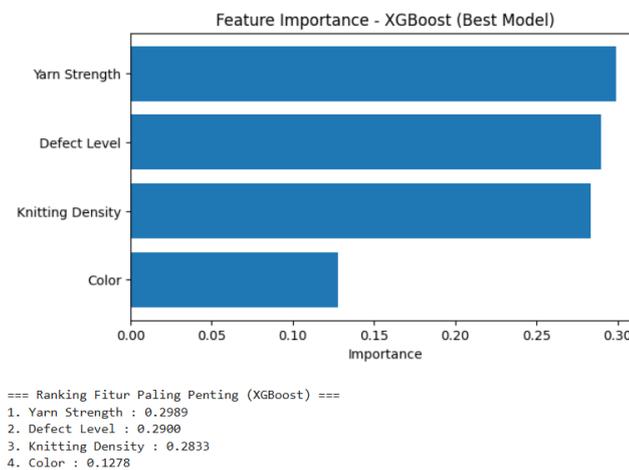


Figure 10. Feature Importance and Interpretability Analysis

These findings are consistent with textile production logic, where mechanical strength, structural density, and defect presence play dominant roles in determining product quality. To further support interpretability, SHAP analysis was employed to examine the contribution of individual features to model predictions, enabling QC personnel to understand not only which features are important, but also how they influence eligibility decisions.

3.9 Hyperparameter Optimization Results

Hyperparameter tuning was performed using GridSearchCV integrated with cross-validation. The optimal parameter configuration identified includes learning_rate = 0.1, max_depth = 3, n_estimators = 500, subsample = 0.8, and colsample_bytree = 0.8.

```
Best params: {'colsample_bytree': 0.8, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 500, 'subsample': 0.8}
```

Figure 11. Hyperparameter Optimization Results

This configuration achieved the best balance between model complexity and predictive performance. The tuned XGBoost model consistently outperformed untuned configurations, demonstrating improved stability and generalization across all validation folds.

3.10 Industrial Implications

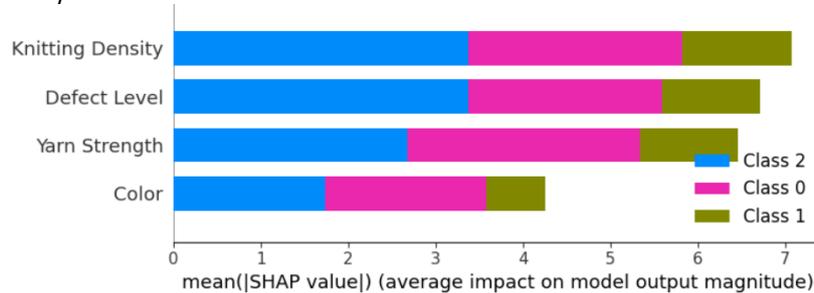


Figure 12. Shap (Model Interpretability)

From an industrial quality control perspective, the proposed model provides both high predictive accuracy and explainable insights. The ability to accurately identify Not Eligible products supports early defect prevention, reduces rework costs, and enhances overall QC efficiency. Moreover, the interpretability provided by feature importance and SHAP analysis enables decision-makers to trace quality issues back to specific production factors, supporting targeted corrective actions in textile manufacturing.

4. CONCLUSION

This study concludes that the XGBoost algorithm demonstrates excellent and stable performance in classifying textile product eligibility using real Quality Control (QC) data from PT ABC Textile. By employing stratified 5-fold cross-validation, the proposed model achieves a high and consistent mean F1-score of 0.985 with low variance across validation folds, indicating strong generalization capability even under class imbalance conditions. Hyperparameter optimization using GridSearchCV resulted in an optimal configuration that balances model complexity and predictive performance. The tuned XGBoost model achieved an overall accuracy of approximately 0.99, with class-wise precision, recall, and F1-score values consistently exceeding 0.95. Notably, the model demonstrated particularly strong performance in identifying Not Eligible products, which is critical for minimizing quality risks and preventing defective products from entering downstream production or distribution stages. Beyond predictive accuracy, this research highlights the importance of model interpretability for industrial quality control applications. Feature importance and SHAP-based analysis reveal that Yarn Strength, Defect Level, and Knitting Density are the most influential factors in determining product eligibility, providing actionable insights for QC personnel. These findings enable more informed decision-making by linking model predictions to specific production parameters that can be adjusted or improved. Overall, this study does not propose a new classification algorithm but positions XGBoost as an interpretability-driven decision-support tool for textile quality control. The proposed approach

supports early defect detection, reduces rework costs, and enhances the reliability of QC evaluations. Future research may explore larger datasets, cost-sensitive learning, and integration with real-time production systems to further strengthen the industrial applicability of the proposed model.

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