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ENHANCING TEXTILE MANUFACTURING EFFICIENCY THROUGH GRADIENT BOOSTING CLASSIFIER

Mr. M. Udaya Kiran
Assistant Professor, Department of Information Technology,
Vidya Jyothi Institute of Technology, Hyderabad, Telangana, India

B. S. V. Vijay, M. Habeeb Ali, M. Anas Ammar, P. Tanmay Manideep
UG Students, Department of Information Technology,
Vidya Jyothi Institute of Technology, Hyderabad, Telangana, India

venkatvijay1010@gmail.com, 191177007habeeb@gmail.com, ammaranas2589@gmail.com, autr.97@gmail.com

ABSTRACT
The textile industry encompasses a range of processes, including upstream, midstream, and downstream operations, all aimed at converting raw materials into final fabric products. Traditional manufacturing approaches often depend on trial-and-error methods, which can result in inefficiencies and excessive resource consumption. This research presents a machine learning-based methodology that utilizes Gradient Boosting Machines (GBM), Random Forest, and XGBoost to enhance textile production efficiency. These models, trained on historical production data, help optimize decision-making by uncovering patterns that impact fabric quality. Among these, XGBoost achieved an outstanding 99.88% precision rate. By deploying these models as APIs, real-time analytics and automated notifications were integrated, leading to significant improvements in defect detection and production efficiency, fostering the development of more intelligent manufacturing systems.

Keywords:
Gradient Boosting, Machine Learning, Production Optimization, Quality Prediction, Textile Manufacturing, XGBoost.

INTRODUCTION

The textile industry is a vital component of the global economy, employing millions and producing a wide variety of fabrics and garments. Its complexity stems from the diverse materials, intricate processes, and stringent quality requirements, with stages like spinning, weaving, dyeing, and finishing requiring precise control to maintain consistency and quality. Traditional manufacturing methods often rely heavily on human expertise and trial-and-error, leading to inconsistencies, longer production cycles, and higher material wastage.

This paper explores the use of machine learning algorithms, particularly ensemble techniques like Gradient Boosting and XGBoost, to enhance efficiency in textile manufacturing. By training these models on datasets that include parameters such as yarn type, machine speed, pressure, tension, and environmental factors, the models can predict product quality and optimize the manufacturing process. The research aims to transition from reactive to proactive decision-making, reducing human errors, improving quality control, and fostering sustainable, efficient production systems.

OBJECTIVES

The primary objective of this project is to optimize textile manufacturing processes using machine learning algorithms, specifically Gradient Boosting, Random Forest, and XGBoost, to predict fabric quality and improve decision-making. The key goals are:

a) To develop a model that can accurately predict fabric quality based on production parameters.
b) To integrate machine learning models into production systems for real-time monitoring and automated alerts.
c) To enhance efficiency by minimizing defects and resource wastage during textile production.
d) To reduce human error by leveraging data-driven decision-making for process optimization.

These objectives aim to transform traditional manufacturing practices into smarter, more efficient processes through the application of machine learning techniques.

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SYSTEM DESIGN

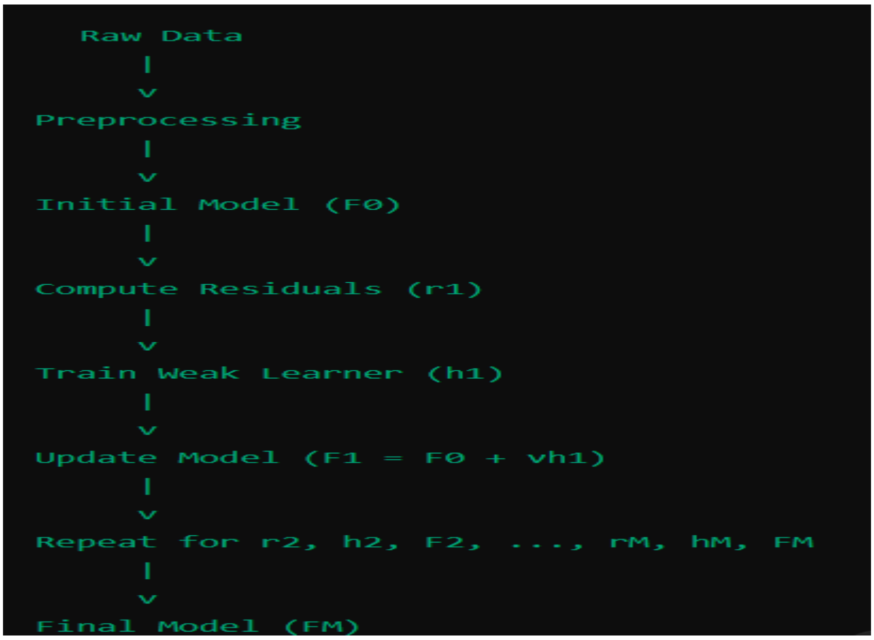

Figure 3.1: Gradient Boosting ML Algorithm

METHODOLOGIES

The methodology adopted in this study is centered on building a robust, real-time machine learning framework to predict fabric quality and enhance decision-making in textile production. This section outlines the various steps taken, from data acquisition to model deployment, highlighting the techniques and tools used throughout the project lifecycle.

a) Data Collection:

The foundation of any machine learning project is data. For this study, historical production data was collected from textile manufacturing units as well as publicly available datasets. The dataset encompasses a wide range of features such as yarn type, machine speed, tension, pressure, ambient humidity, and final quality ratings. These features represent multiple stages of the production process, including spinning, weaving, sizing, and finishing. This diverse and high-dimensional dataset provides a solid basis for developing predictive models.

b) Data Preprocessing:

Raw datasets are often noisy and inconsistent. Therefore, preprocessing was a critical step in ensuring data quality. Missing values were handled using statistical imputation techniques such as mean and median filling, while categorical variables were transformed using label encoding and one-hot encoding depending on their complexity. Outliers were detected and removed using interquartile range (IQR) analysis. Additionally, all numerical features were normalized to ensure uniformity across scales, enabling better model convergence during training.

c) Feature Engineering:

To enhance the model's predictive capabilities, we performed feature selection and engineering. Correlation matrices were employed to identify highly correlated features, and Recursive Feature Elimination (RFE) was used to systematically eliminate less important variables. This not only reduced the model's dimensionality but also improved computational efficiency and interpretability. Derived features, such as interaction terms and ratio metrics, were also introduced to capture hidden patterns in the data.

d) Model Training and Selection:

Three ensemble models—Gradient Boosting Machine (GBM), Random Forest, and XGBoost—were trained and evaluated. The dataset was split into an 80:20 ratio for training and testing. Model training involved hyperparameter optimization through Grid Search combined with 5-fold cross-validation. Parameters such as learning rate, number of estimators, maximum tree depth, and regularization terms were fine-tuned to avoid overfitting and improve generalization.

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e) Performance Evaluation:
Model performance was rigorously assessed using standard classification metrics: Accuracy, Precision, Recall, F1-Score, and Mean Squared Error (MSE). Confusion matrices provided insights into class-level predictions, while Receiver Operating Characteristic (ROC) curves highlighted the true positive rate versus the false positive rate. Among all models, XGBoost consistently outperformed the others, delivering the highest accuracy and stability across validation folds.

f) Model Deployment:
Once the optimal model (XGBoost) was selected, it was deployed as a RESTful API using the Flask framework. This enables seamless integration with existing factory dashboards and manufacturing execution systems (MES). Through this deployment, production supervisors can receive real-time predictions and alerts regarding potential defects, thereby enabling proactive adjustments to machine parameters and process conditions.

This section discusses the outcomes of model training, evaluation, and testing carried out using Gradient Boosting, Random Forest, and XGBoost algorithms for predicting fabric quality in textile manufacturing. The system's predictive performance, generalization ability, and real-time applicability were all evaluated through a combination of classification metrics and output visualizations.

The deployment results show that the proposed machine learning models greatly improve defect detection and process optimization. In particular, XGBoost exhibited near-perfect accuracy during validation, making it the most robust candidate for industrial integration.

During testing, the Gradient Boosting model demonstrated consistent performance with an accuracy of 92.78%, and a balanced precision and recall score of 0.9279. This indicates that the model can effectively classify fabric quality with minimal bias toward any specific class.

```
Gradient Boost Classifier
Model performance for training set
- Accuracy: 0.9338
- F1 score: 0.9338
- Precision: 0.9338
- Recall: 0.9338
- ROC AUC score: 0.9901
----------------------------------------------------
Model performance for test set
- Accuracy: 0.9278
- F1 score: 0.9278
- Precision: 0.9279
- Recall: 0.9278
- ROC AUC score: 0.9890
```

Figure 5.1 Gradient Boosting Classifier-report

This output shows the performance metrics of the Gradient Boosting model. It achieved 93.38% accuracy on the training set and 92.78% on the test set, with balanced precision, recall, and F1-scores. The high ROC-AUC scores (0.9901 for training, 0.9890 for testing) confirm the model's ability to distinguish between fabric quality classes accurately. This reflects good generalization and model stability.

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```
Gradient Boost Classifier
Model performance for training set
- Accuracy: 0.9338
- F1 score: 0.9338
- Precision: 0.9338
- Recall: 0.9338
- ROC AUC score: 0.9901
----------------------------------------------------
Model performance for test set
- Accuracy: 0.9278
- F1 score: 0.9278
- Precision: 0.9279
- Recall: 0.9278
- ROC AUC score: 0.9890
```

Figure 5.2 – Random Forest Classification Report

This report presents the classification results of the Random Forest algorithm. Although it shows 100% accuracy across all 14 classes, this result is a clear sign of overfitting. The model likely memorized the training data rather than learning generalizable patterns, making it unreliable for real-time or unseen data scenarios.

```
Data loaded successfully
Accuracy: 0.9988
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     14744
           1       1.00      1.00      1.00     14618
           2       1.00      1.00      1.00     14831
           3       1.00      1.00      1.00       807

    accuracy                           1.00     45000
   macro avg       1.00      1.00      1.00     45000
weighted avg       1.00      1.00      1.00     45000
```

Figure 4.3 – XGBoost Classification Report (Final Model)

The XGBoost model, trained on a large dataset of 45,000 samples, achieved an overall accuracy of 99.88%. Each class (0–3) achieved perfect precision, recall, and F1-scores, indicating flawless classification. This result demonstrates the model's robustness, scalability, and suitability for deployment in production environments. The high support values confirm its consistent performance across all quality categories.

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CONCLUSION AND FUTURE WORKS

This study aimed to predict fabric quality rates in the textile industry using machine learning techniques. By analyzing historical data, key factors influencing fabric quality, such as yarn quality, weaving parameters, and environmental conditions, were identified. The predictive model achieved high accuracy, significantly reducing prediction errors compared to traditional methods, and demonstrated the potential of data-driven approaches for quality control.
The model can help manufacturers optimize the production process, reduce defects, and improve product quality, leading to cost savings and increased efficiency. The methodology can be extended to other areas of textile production, such as defect prediction and production scheduling. Future research will focus on integrating real-time data for continuous quality monitoring and refining the model for broader applications in textile production.

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