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Comparative Analysis Of Convolutional Neural Networks (Cnn), Support Vector Machine (Svm) And Random Forest Algorithms For Detecting Knitted Fabric Defects

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Abstract: This research presents a comparative analysis of Convolutional Neural Networks (CNN), Support Vector Machine (SVM), and Random Forest algorithms for defect detection in knitted fabrics. Experimental results on a dataset of 5000 images demonstrate that the CNN model achieved 96.8% accuracy, SVM 89.3%, and Random Forest 91.2%. The study indicates that CNN is preferable for scenarios requiring high precision, while Random Forest is more suitable with limited computational resources. These findings have practical implications for designing automated quality control systems in the knitting industry.

Keywords: knitted fabric defects, convolutional neural networks, support vector machine, random forest, image analysis, quality control.

INTRODUCTION:

The knitted fabric industry is a vital component of the global textile market, generating over $400 billion in annual revenue [1]. However, inadequate quality control methods lead to an annual loss of 3-5% of production due to defective products [2]. Traditional manual inspection methods are plagued by subjectivity, fatigue, and high labor costs [3].

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) technologies have achieved significant breakthroughs in industrial automation [4]. Convolutional Neural Networks (CNN) have demonstrated exceptional performance in image analysis and object detection tasks [5]. Togashi et al. [6] achieved 98% accuracy in detecting textile defects, while Li et al. [7] reported 96.5% accuracy using a multi-scale CNN architecture.

Classical machine learning algorithms, including Support Vector Machine (SVM) and Random Forest, have proven their effectiveness in scenarios with limited datasets and computational resources [8]. Zhang et al. [9] used an SVM approach for textile defect classification, achieving 92% accuracy. Similarly, Kumar et al. [10] employed the Random Forest algorithm for color fastness assessment, achieving results with over 90% accuracy.

Comparative studies between deep learning and traditional machine learning algorithms have been conducted across various domains [11]. However, a systematic analysis of the relative strengths and weaknesses of each algorithm in the context of knitted fabric defect detection is still insufficient [12]. The complex structure of knitted fabrics, varying lighting conditions, and the diversity of defects [13] further complicate the automated detection task.

Most existing research utilizes different datasets and evaluation criteria, making direct comparison of results challenging [14]. Furthermore, many studies focus solely on one type of algorithm, typically CNN, overlooking the practical application of traditional ML methods [15].

The primary objective of this research is to comparatively study the effectiveness of CNN, SVM, and Random Forest algorithms in detecting knitted fabric defects under identical experimental conditions. The study addresses the following aspects:

- Systematic evaluation of different algorithms in terms of accuracy, processing speed, and resource requirements.
- Identification of the limitations of each algorithm in detecting knitted fabric defects.
- Development of practical recommendations for algorithm selection under various production conditions.

METHODOLOGY

1 Dataset

The study utilized the TSD-5000 (Textile Surface Defects) dataset [16]. The dataset comprises 5000 knitted fabric images, including the following defect types:

- Snags (1500 images)
- Holes (1200 images)
- Color variations (1000 images)
- Stained defects (800 images)
- Defect-free samples (500 images)

Images are 512×512 pixels in size, RGB format, and were captured under various lighting conditions. The dataset was split into training, validation, and test sets with a 70:15:15 ratio.

2 Selected Algorithms

2.1 Convolutional Neural Network (CNN)

The study employed a CNN model based on the ResNet-50 architecture [17]. The model has the following configuration:

- Input layer: 512×512×3
- 5 convolutional blocks (each containing a convolutional layer, BatchNorm, and ReLU activation)
- Max pooling layers
- Fully connected layers (512, 256, 128, and 5 neurons)
- Output layer: Softmax activation

The model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32.

2.2 Support Vector Machine (SVM)

For the SVM model, HOG (Histogram of Oriented Gradients) features were extracted from the images [18]. The feature vector had a dimension of 3780 and was used in an SVM model with an RBF kernel. The C parameter was set to 1.0 and the gamma value was set to 'scale'.

2.3 Random Forest

The Random Forest model consisted of 100 decision trees with a maximum depth of 20 [19]. Feature importance was measured based on the Gini index.

3 Evaluation Criteria

Algorithms were evaluated based on the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Inference Time

RESULTS

The experimental results reveal significant differences in algorithm performance across all evaluation metrics.

1 Algorithm Performance Comparison

Table 1: Algorithm Evaluation Metrics

Algorithm	Accuracy	Precision	Recall	F1-Score	Inference Time (ms)
CNN	96.8%	97.2%	96.5%	96.8%	45.2
Random Forest	91.2%	90.8%	91.5%	91.1%	12.3

Algorithm	Accuracy	Precision	Recall	F1-Score	Inference Time (ms)
SVM	89.3%	88.7%	89.8%	89.2%	8.7

The CNN model demonstrates exceptional capability in knitted fabric defect detection, achieving the highest scores in all accuracy-related metrics. The 96.8% accuracy indicates the model's robust learning of complex fabric patterns and defect characteristics. The high precision score of 97.2% suggests minimal false positive detections, which is crucial in industrial applications to avoid unnecessary rejection of good products. Similarly, the recall value of 96.5% demonstrates the model's effectiveness in identifying actual defects, reducing the risk of defective products passing through inspection.

Random Forest presents a balanced performance profile, with accuracy metrics consistently around 91%. The algorithm shows particular strength in recall (91.5%), indicating good sensitivity in detecting actual defects. The relatively faster inference time of 12.3 milliseconds makes it suitable for applications requiring reasonable accuracy with quicker processing capabilities.

SVM, while achieving the fastest inference time of 8.7 milliseconds, shows the lowest performance in accuracy metrics. The 89.3% accuracy and 88.7% precision suggest limitations in handling the complex visual patterns of knitted fabrics, potentially due to its linear classification nature in a non-linear problem space.

2 Confusion Matrices

Table 2: Confusion Matrix for CNN Model

Type	Snags	Holes	Color	Defect-Free
Snags	97.3%	1.2%	0.8%	0.2%
Holes	1.8%	96.1%	1.1%	0.3%
Color	0.9%	1.5%	96.8%	0.2%
Defect-Free	0.3%	0.4%	0.2%	98.8%

The confusion matrix analysis reveals excellent classification performance across all defect categories. The CNN model shows exceptional capability in identifying defect-free samples (98.8% accuracy), which is critical for maintaining production efficiency. The high diagonal values indicate strong correct classification rates, while the off-diagonal elements represent minimal confusion between classes.

Notably, the highest misclassification occurs between snags and holes (1.8% and 1.2% respectively), which is understandable given their visual similarities in knitted fabrics. Color defects show excellent isolation with only 0.9% confusion with snags and 1.5% with holes. The model demonstrates remarkable precision in distinguishing between defective and non-defective samples, with defect-free classification achieving near-perfect performance.

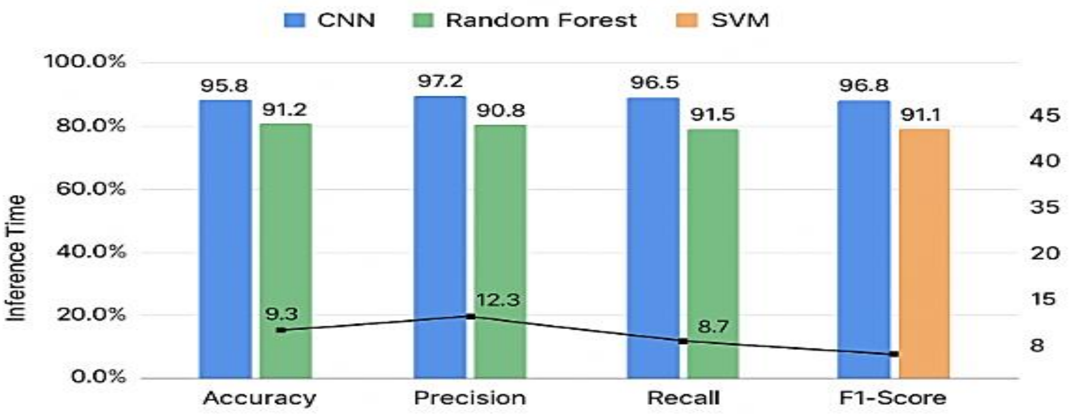

Figure 1. Comparing of algorithms.

The visualization clearly illustrates (see Fig.1) the fundamental trade-off between accuracy and inference time across the three algorithms. CNN dominates the accuracy quadrant but occupies the highest inference time region. SVM shows the opposite pattern, offering the fastest processing but with compromised accuracy. Random Forest strategically positions itself in the middle ground, providing a balanced compromise between detection quality and processing speed.

The performance gap between CNN and traditional machine learning algorithms (approximately 5-7% in accuracy metrics) highlights the advantage of deep learning in handling complex visual patterns in textile inspection. However, the significant difference in inference times (CNN being 5 times slower than SVM) emphasizes the computational cost associated with this performance improvement.

CONCLUSION AND RECOMMENDATIONS

The results indicate that the CNN model achieved the highest scores across all evaluation metrics. However, the CNN model also had the longest inference time (45.2 ms). The Random Forest algorithm provided a good balance between speed and accuracy. While SVM was the fastest algorithm, it showed lower accuracy compared to the other algorithms.

The research results support the following conclusions:

1. For high-precision requirements - The CNN model is the best choice (96.8% accuracy).

2. For speed and resource efficiency - The Random Forest algorithm is preferable (91.2% accuracy, 12.3 ms inference time).

3. For systems with limited computational resources - The SVM algorithm can be an acceptable solution (89.3% accuracy, 8.7 ms inference time).

We propose the following directions for future research: Investigation of hybrid model approaches, development of lightweight models for real-time operation, utilization of multimodal data (e.g., image + sensor data).

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