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Secretary Bird Optimised Support Vector Machine Model For Adire Fabric Defect Detection

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ABSTRACT

Adire fabric is a traditional hand-dyed fabric indigenous to the Yoruba people of Nigeria. It is produced using manual resist-dyeing techniques involving materials such as raffia, wax, starch, or stitching. These handcrafted processes while culturally significant, make the fabric highly susceptible to a variety of defects such as stains, tears, pattern misalignment, colour variation, colour crocking, sulphur-mark and, colour-smear. Traditional visual inspection methods are labour-intensive, time consuming and prone to error. Hence, this study developed an optimised Support Vector Machine (SVM) model using the Secretary Bird Optimisation Algorithm (SBOA) for automated detection of Adire fabric defects. 234 Adire fabric images were acquired using a Redmi 14C 50MP digital camera and augmented to 884. Among the data collected, 396 images represented various type of defects while 488 were non-defective (Normal). Preprocessing involved Gaussian filtering and Contrast Limited Adaptive Histogram Equalisation (CLAHE), while Gray-Level Co-occurrence Matrix (GLCM) was used for texture-based feature extraction. SBOA was applied to optimise SVM hyperparameters (penalty factor C, kernel type, gamma (γ), and polynomial degree) yielding the SBOA-SVM model, implemented in MATLAB R2023a. The performance of the model was evaluated against standard SVM using accuracy, sensitivity, specificity, false positive rate as metrics. SBOA-SVM outperformed standard SVM across all defect categories. For colour crocking and colour smear, SBOA-SVM achieved accuracy of 95.81% and 96.04%, and sensitivity of 85.29% and 85.61%, respectively, while the corresponding values obtained for standard SVM were 93.55% and 94.23%. Challenging defects like colour variation, tear, and stain, SBOA-SVM improved sensitivity to 70.45%, 72.73%, and 72.50% at specificity above 98%. The developed SBOA-SVM model demonstrated superior accuracy and efficiency, establishing its potential for automated defect detection in Adire and other related textile applications.

INTRODUCTION

Africa fabrics are mostly hand crafted. African fabric artisans employ different styles and techniques such as dyeing, weaving and painting with the hand to make various intricate weaving and dyeing finishes on fabric in order to make a fashion statement. This, invariably makes their work of fabric making susceptible to defects. Adire is a creative patterned dyed fabric indigenous to the Yoruba people of Nigeria. Its production involves a resist-dyeing technique which utilises different methods such as Raffia Resist (Adire Oniko), Stitch Resist (Adire Alabere), Wax Resist (Adire Alabela), and Starch Resist (Adire Eleko) (Ojelade *et. al.*, 2018). The last two methods are now referred to as Batik and all of these four methods of Adire production are achieved locally with the hand thus, defects are inevitable. Fabric defects can be classified into major and minor defects. Major defects are conspicuous on the finished product and affect its usability or even shorten the life cycle of the fabric while a minor defect is not likely to reduce the usability of the fabric but could negatively influence the sales. Common defects in Adire fabrics include stains, tear, colour variation, colour smear, and colour crocking. In the Adire fabric production, identifying and classifying defects has not been really considered or put to practice; even when done, a manual visual assessment method that lacks efficiency is been employed. The detection results, many times, are overlooked or hidden by the artisans and left for the retailers or end-users to manage the consequences (Olagunju et al, 2025).

There are different contemporary defects detection systems using image processing and machine learning techniques which would reduce fabric wastage and improve profitability (Charkraborty *et al.*, 2021; Atanda et al 2023). SVM is a highly effective supervised learning algorithm widely used for classification, regression, and outlier detection tasks (Mustapha et al., 2025). SVM identifies the optimal separating hyperplane between different classes, providing a solution to the classification problem (Awad and Khanna, 2015; Adetunji et al., 2015; Ige et al., 2025). However, SVM parameters can be improved using metaheuristic algorithms such as Grey Wolf Optimisation (GWO), Whale Optimisation Algorithm (WOA), and Moth Flame Optimisation (MFO) and Secretary Bird Optimisation Algorithm (SBOA) for optimizing SVM parameters (Abbaszadeh *et al.*, 2022; Adetunji et al., 2018). Secretary Bird Optimisation Algorithm SBOA is an algorithm inspired by the Secretary bird's hunting and escape strategies; exploration phase simulates the bird's hunting of snakes while exploring different areas of the search space while the exploitation phase models the bird's escape from predators, focusing on refining solutions within a promising region. SBOA is well-suited for SVM models due to its effective balance of search space which is important for maximizing SVM performance. While SBOA has been successfully applied across diverse fields such as image classification, text classification, and bioinformatics (Fu, 2024) this study, leverages SBOA to optimise SVM for defect detection on the created Adire fabric dataset. SBOA was selected specifically for its documented outstanding performance regarding convergence speed, accuracy, and efficient balance between exploration and exploitation tasks. Hence, this study utilised SBOA optimised SVM to develop an automated Adire defect detection model.

The proposed technique has the following contributions:

(i) The study acquired Adire fabric images from Adire artisans with a Redmi 14C 50MP digital camera and created a dataset for it;

(ii) The study introduced SBOA as a novel metaheuristic for optimising SVM parameters in Adire fabrics defects detection;

(iii) The performance evaluation of the proposed model was carried out in comparison with a standard SVM using accuracy, sensitivity, specificity, false positive rate, and detection time as metrics;

The study validates SBOA-SVM against standard SVM for Adire defects detection

REVIEW OF RELATED WORKS

This section presents studies that have contributed to advancements in automated defect detection systems. Overtime, researchers have progressed to machine learning techniques and artificial intelligence methods which aim to exceed human inspection capabilities in terms of speed and precision. Halimi *et al.* (2014) developed an automated defect detection and classification system for fabrics using Support Vector Machines. The problem identified was the inconsistent identification of defects such as holes and yarn misalignments. The methodology involved grayscale image acquisition, histogram equalisation for contrast enhancement, Otsu thresholding for segmentation, and geometric feature extraction followed by SVM classification.

The system achieved a classification accuracy of 96.15%, showing its effectiveness in distinguishing fabric defects. However, it has a tendency to misclassify defects with similar geometric characteristics, which could affect its generalisation in diverse fabric types. Also, Awad and Khanna in 2015 examined the theoretical and practical applications of SVMs in pattern recognition, particularly their strengths in handling high-dimensional data. The study demonstrated that kernel functions enhance SVM's flexibility in modelling nonlinear relationships and confirmed its high classification accuracy across diverse tasks. Nonetheless, its limitation was the need for careful hyperparameter tuning, especially the choice of kernel and regularisation parameters, which significantly impact model performance. Xing *et al.* (2017) proposed a system for automated fabric defect detection using wavelet transform and Principal Component Analysis (PCA). The goal was to develop a robust feature extraction and classification pipeline. It applied wavelet transforms for multi-resolution analysis and PCA for dimensionality reduction before classification. The model achieved high accuracy in identifying standard defect types. However, it struggled with new or subtle defect patterns, limiting adaptability, especially in cases requiring learned, high-level features typical of deep learning approaches. Abbaszadeh *et al.* (2022) aimed to improve the reliability of SVMs in pattern recognition tasks by addressing the issue of manual hyperparameter tuning, which often results in suboptimal performance by using metaheuristic algorithms to optimise the critical parameters of SVM, such as kernel type and regularisation constants by integrating Particle Swarm Optimisation (PSO) and Grid Search techniques to automate parameter selection. The results indicated a notable improvement in classification accuracy and robustness across several datasets. However, this comes with increased computational complexity and the need for domain-specific knowledge to configure the optimisation algorithm effectively. Adio *et al.* (2024) introduced a deep learning-based method for fabric defect classification to address the challenge of unreliable manual inspection in textile manufacturing. Their objective was to create an optimised deep learning model using the Osprey Optimisation Algorithm (OOA); a metaheuristic algorithm inspired by the behaviour of ospreys to enhance classification accuracy. The results showed significant improvements in defect detection accuracy and classification efficiency but comes with high computational cost associated with metaheuristic optimisation, which could hinder real-time application in high-speed industrial environments.

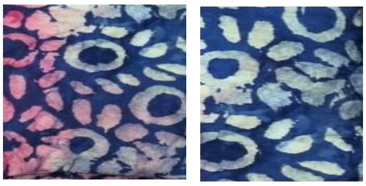
METHODOLOGY

The steps involved in the development of Secretary Bird Optimised Algorithm based Support Vector Machine (SBOA-SVM) model for Adire fabric defect detection are data acquisition, preprocessing, feature extraction, defect detection and performance evaluation.

Data Acquisition

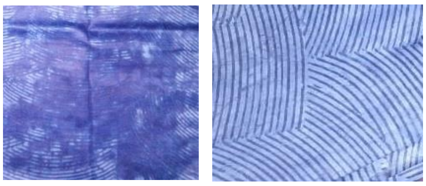
A dataset of 234 Adire fabric images were acquired using a Redmi 14C 50MP digital camera and augmented to 884 images through flipping and rotation to increase the dataset size and enhance model generalisation. Out of the total dataset, 488 were non-defective (Normal (N)) Adire fabrics while 396 were defective (136 Colour Crocking (CC), 132 Colour Smear (CS), 44 Colour Variation (CV), 44 Tear (T) and 40 Stain (S)). For model training and testing, the K-fold cross-validation approach was employed with K (number of folds) = 10 to ensure an unbiased partitioning of the dataset into training and testing subsets.

(a) Stain Non-defective (Normal)

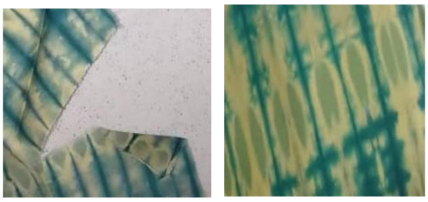


(b) Colour Variation Non-defective (Normal)

(c) Colour Smear Non-defective (Normal)



(d) Colour Crocking Non-defective (Normal)



(e) Tear Non-defective (Normal)

Plate 1: Sample of Acquired Images of Defects and Non-Defective (Normal) Adire Fabrics

Preprocessing

The acquired raw images were first preprocessed before being used as input for feature extraction. Noises were removed from the image signal using Gaussian filter and the images were enhanced with Contrast Limited Adaptive Histogram Equalisation (CLAHE) in MATLAB. CLAHE is an enhanced version of histogram Equalisation (HE), which is a simple and effective image enhancement method that can increase the contrast of images by adjusting the image's gray distribution in order to enhance defect detectability and improve model performance during detection (Oguntoye et al., 2025).

Feature Extraction

Gray-Level Co-occurrence Matrix (GLCM) was used to extract second-order texture features such as contrast, correlation, energy and homogeneity from each fabric image. The resulting matrix was then used to extract statistical features that describe texture properties that the machine learning model used for distinguishing defective regions from defect-free areas (Ogundepo et al., 2022; Olayiwola et al., 2023). Feature extraction helps to reduce complexity of the image data by extracting the most discriminative information thereby improving the reliability defect detection system.

Design of Optimised SVM using SBOA

The Secretary Bird Optimised Support Vector Machine (SBOA-SVM) model was designed to enhance the detection of fabric defects by optimally tuning the hyperparameters of the Support Vector Machine (SVM) using the Secretary Bird Optimisation Algorithm (SBOA). The SVM algorithm aims to construct an optimal hyperplane that separates defective from non-defective samples. However, the performance of SVM is highly sensitive to its parameters such as the penalty factor (C), kernel type, and kernel-specific parameters (e.g., gamma and polynomial degree). Improper tuning of these parameters can lead to underfitting or overfitting. SBOA addresses this challenge by employing a bio-inspired search mechanism that adaptively explores the parameter space for optimal configurations.

Formally, the SVM minimises the cost function:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{1}$$

Subject to:

$$y_i(w^T\varphi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \tag{2}$$

where $\varphi(x)$ is the kernel transformation, C is the penalty parameter, and ξ_i are slack variables allowing soft-margin classification. The kernel functions employed include:

i. Linear: $K(x, x') = x^T x'$

ii. RBF: $K(x, x') = \exp(-\gamma\|x - x'\|^2)$

iii. Polynomial: $K(x, x') = (\gamma x^T x' + r)^d$

iv. Sigmoid: $K(x, x') = \tanh(\gamma x^T x' + r)$

Secretary Bird Optimisation Algorithm (SBOA)

The Secretary Bird Optimisation Algorithm (SBOA) is inspired by the hunting behaviour of the secretary bird, which exhibits precise and adaptive attacks. As shown in algorithm 1, each bird represents a candidate solution (parameter set) consisting of SVM hyperparameters. The algorithm iteratively refines these parameters to maximise detection accuracy. Through iterative updates, the algorithm converges on the optimal SVM parameter set $X_{\text{best}} = [C^*, K^*, \gamma^*, d^*]$, which maximises the detection performance. The resulting SBOA-SVM model is then trained on the complete training dataset and evaluated using performance metrics such as sensitivity, specificity, accuracy, false positive rate, and detection time.

Algorithm 1

Step1: Initialisation N: number of birds (population size) D: number of parameters to optimise (C, kernel type, γ, degree)

$X_i \in \mathbb{R}^D$: position vector of bird i

T: maximum number of iterations Bounds for parameters:

$$C \in [0.1,1000]$$
$$Y \in [0.0001,1]$$

kernel type ∈ {0,1,2,3}

degree ∈ {2,3,4,5}

Randomly initialise positions $X_i, i = 1, \ldots, N$

Step 2: Fitness Function

Each bird (solution) represents:

$$X_i = [C_i, K_i, \gamma_i, d_i]$$

Train an SVM using parameters decoded from X_i and evaluate detection accuracy as:

$$\text{Fitness }(X_i) = \text{ DetectionAccuracy }(X_i)$$

Step 3: Secretary Bird Position Update Equation

$$X_i \wedge (t+1) = X_i \wedge t + \alpha \cdot \sin(\phi) \cdot (X_i \text{ best } \wedge t - X_i \wedge t) + \beta \cdot r \cdot \left(X_i \wedge t - X_j \wedge t\right)$$

Where:

$\phi \in [0,2\pi]$: random angle

$r \in [0,1]$: random scalar

X_best^t : best bird at iteration t

$X_j \wedge t$: randomly chosen neighbor of i

$$\alpha = A \cdot (1 - t/T), \beta = B \cdot (t/T), A = B = 2$$

Step 4: Parameter Decoding and Handling Discrete Variables

Kernel type K : rounded to nearest integer ∈ {0,1,2,3}

Polynomial degree d : rounded ∈ {2,3,4,5}

Gamma γ is only active for RBF, polynomial and sigmoid kernels

Apply bounding rules after update:

$X_i \wedge (t+1) = \min(\max(X_i \wedge (t+1),$ lower_bound), upper_bound)

Step 5: Termination Criteria Repeat Steps 2-4 until:

Maximum iterations reached ($t = T$), or No improvement for K generations
Step 6: Output
Best solution: X_best = [C^*, K^*, γ^*, d^*]
Train final SVM model using optimised parameters
Evaluate detection performance on the test dataset

Implementation of the Proposed SVM-SBOA

The system was implemented in MATLAB (R2023a) on window 10 ultimate 64bit operating system, intel core i7 CPU with a speed of 4.4GHz, 8GB RAM and 1 Terabyte hard disk drive to detect the fabric defects and evaluate the performance of the system. An interactive GUI application with Adire datasets was designed using MATLAB's GUI toolbox. The detection process with SBOA-SVM in MATLAB involved data collection and preprocessing. Parameters were initialized, and SBOA-SVM optimized the system, followed by parameter tuning within the MATLAB environment, with performance evaluation conducted using various metrics.

Performance Evaluation

The last phase of building the model is to make some predictions and evaluate the performance of the developed SBOA-SVM model in comparison with standard SVM using these metrics: False Positive Rate (FPR), Specificity, Sensitivity and Accuracy to validate the model. These metrics collectively assess the ability of the model to correctly detect defective fabrics while minimising false alarms.

False Positive Rate (FPR)

The False Positive Rate represents the proportion of non-defective fabric samples incorrectly detected as defective.

$$FPR = \frac{FP}{FP+TN} * 100\% = 1 - Specificity \quad (3)$$

Specificity (True Negative Rate): Measures the ability of the model to correctly identify non-defective fabrics.

$$\text{Specificity} = \frac{TN}{TN+FN} * 100\% \quad (4)$$

Sensitivity (True Positive Rate): Represents the model's ability to correctly detect fabrics that are actually defective.

$$\text{Sensitivity} = \frac{TP}{TP+FN} * 100\% \quad (5)$$

Accuracy: Indicates the overall correctness of the model's detections.

$$\text{Accuracy} = \frac{TN+TP}{FN+FP+TN+TP} * 100\% \quad (6)$$

Detection Time: Represents the average time (in seconds or milliseconds) required by the model to process and detect a defect in a single fabric image.

RESULTS AND DISCUSSION

Analytical results

The experimental results for the Adire defects detection using SBOA-SVM model were presented through a custom-built Adire Fabric Defect Detection System. The Graphical User Interface (GUI) shown in Figure 2 and Figure 3 enabled the training and testing of the system in an interactive environment. The performance of the developed detection system was further analysed with respect to different defect categories in the dataset represented with examples illustrated in Figure 1, where six (6) classes of fabric qualities are shown: colour crocking, colour smear, colour variation, tear, stain, and normal fabrics. The dataset was partitioned using the K-fold cross-validation approach (k = 10) to ensure reliability and unbiased model evaluation during defect detection. The SBOA-SVM model effectively differentiated between defective and non-defective fabrics, ensuring accurate detection even for subtle and overlapping defect patterns.

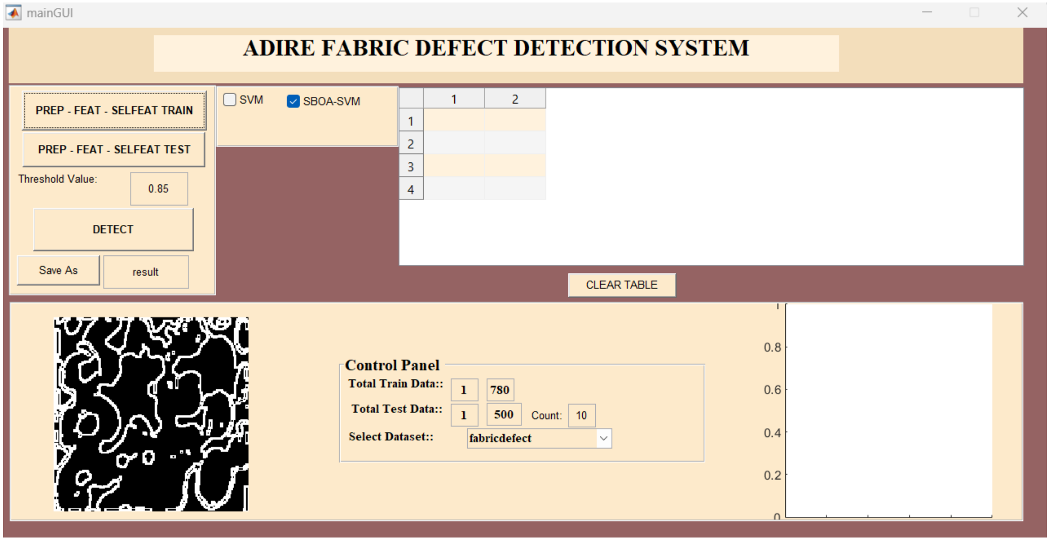


Figure 2: Graphical User Interface of the Adire Fabric Defect Detection System (Training Process)

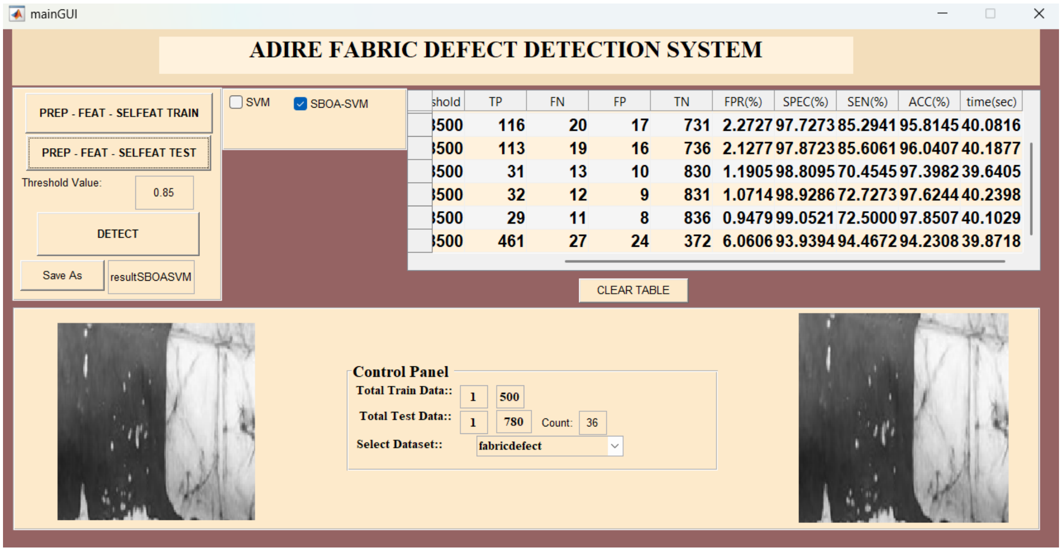


Figure 3: Graphical User Interface of the Adire Fabric Defect Detection System (Testing Process)

Detection Results with SBOA-SVM

The optimised Secretary Bird Optimisation Algorithm based Support Vector Machine (SBOA-SVM) produced superior results, as presented in Table 1. In the colour crocking category, sensitivity improved from 77.94% to 85.29%, and overall accuracy increased from 93.55% to 95.81%. Similarly, colour smear achieved 85.61% sensitivity and 96.04% accuracy, showing that the SBOA parameter tuning effectively strengthened the detection of defective samples. The most substantial improvements occurred in previously challenging defect categories. Sensitivity for colour variation rose from 43.18% to 70.45%, for tear from 47.73% to 72.73%, and for stain from 45.00% to 72.50%. In all cases, specificity exceeded 98%, confirming the optimised model's ability to minimise false alarms while increasing true defect detection rates. The detection time also reduced from ~50s to ~40s per image, indicating a 20%

improvement in computational efficiency without compromising precision.

Detection Results with Standard SVM

The performance of the Support Vector Machine (SVM) for fabric defect detection is presented in Table 2.

Table 1: SBOA-SVM Detection Results

Type of Fabric Defect	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
Colour Crocking	116	20	17	731	2.27	97.73	85.29	95.81	40.08
Colour Smear	113	19	16	736	2.13	97.87	85.61	96.04	40.19
Colour Variation	31	13	10	830	1.19	98.81	70.45	97.40	39.64
Tear	32	12	9	831	1.07	98.93	72.73	97.62	40.24
Stain	29	11	8	836	0.95	99.05	72.50	97.85	40.10
Normal	461	27	24	372	6.06	93.94	94.47	94.23	39.87

Table 2: Standard SVM Detection Results

Type of Fabric Defect	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	ACC (%)	Time (sec)
Colour Crocking	106	30	27	721	3.61	96.39	77.94	93.55	50.06
Colour Smear	105	27	24	728	3.19	96.81	79.55	94.23	50.26
Colour Variation	19	25	22	818	2.62	97.38	43.18	94.68	49.67
Tear	21	23	20	820	2.38	97.62	47.73	95.14	50.25
Stain	18	22	19	825	2.25	97.75	45.00	95.36	50.01
Normal	453	35	32	364	8.08	91.92	92.83	92.42	49.78

The SVM model produced satisfactory accuracies for categories such as colour crocking (93.55%) and colour smear (94.23%), showing strong detection capability for well-defined defects. However, the corresponding sensitivities of 77.94% and 79.55% indicate that several true defects were missed during detection, reflecting the model's limited ability to capture subtle or less prominent anomalies. For challenging defects like colour variation, tear, and stain, the detection performance was notably lower, with sensitivity values of 43.18%, 47.73%, and 45.00%, respectively. Although specificity values remained above 97% for these defect types, the imbalance between sensitivity and specificity shows that the standard SVM tended to misclassify subtle defects as non-defective, resulting in under-detection. The detection of non-defective (normal) fabrics achieved a sensitivity of 92.83% and accuracy of 92.42%, confirming the model's tendency to correctly identify non-defective samples. However, the relatively high false positive rate (8.08%) and an average detection time of approximately 50 seconds across all categories highlight computational inefficiency.

Comparative Analysis of SVM and SBOA-SVM

The comparative analysis between standard SVM and the SBOA-SVM as shown in Table 1 and Table 2 demonstrates clear detection performance gains between the two models. SBOA-SVM significantly outperformed standard SVM, improving sensitivity and accuracy in detecting colour crocking (85.29%, 95.81%) and smear (85.61%, 96.04%). Challenging categories like colour variation, tear, and stain saw major sensitivity gains (43–48% → 70–73%), while specificity stayed above 98%. Normal fabric detection remained stable with 94.47% sensitivity and 94.23% accuracy, though false positives were slightly higher (6.06%). Detection time was reduced to ~40 seconds, showing improved quality without added computational cost. Consequently, SBOA-SVM model provides a practical and efficient solution for industrial-scale fabric defect detection, capable of replacing manual inspection processes.

CONCLUSION

The comparative results decisively establish SBOA-SVM as the improved model for fabric defect detection. While the standard SVM provides a reasonable baseline, its limitations in sensitivity particularly for subtle defects highlight its inability to fully address the challenges of automated fabric inspection. Contrarily, SBOA-SVM achieved higher accuracy, sensitivity, and specificity across all categories, ensuring a more reliable and robust detection system.

The ability to enhance detection performance while reducing computation time demonstrates the practical viability of SBOA-SVM for real-world fabric quality control. Therefore, this study has successfully achieved an improved version of SVM by integrating SBOA to yield a highly effective approach viable for industrial-scale Adire fabric defect detection and real-world textile inspection. The main contributions of this study are highlighted as follows:

i. Creation of Adire dataset
ii. Integration of SBOA into SVM for a robust solution for optimising SVM parameters, leading to a better model performance in handling the intricate patterns characteristic of Adire for defect detection.

The performance evaluation of SBOA-SVM using Accuracy, Sensitivity, Specificity, False Positive Rate (FPR), and Detection Time (DT) as metrics, and compared with that of standard SVM.

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