A Novel Algorithm for Classifying Textile Fiber Using the Proposed Three-Class Support Vector Machine with Matched Filters

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ABSTRACT

This paper introduces a novel approach for classifying textile fibers using near-infrared (NIR) spectra obtained from the NeoSpectra-Micro sensor. The spectra as an input is applied to two matched filters, and each 65th element of both output spectra is used to construct a 2x1 feature vector. The first element is matched for natural fibers, the second elements for synthetic fibers, and both elements for blended fibers. After that, this vector is an input into the proposed three-class classifier based on support vector machine technique to identify textile fibers group. In the experiment to three groups of 210, 480, 270 spectral samples from types of 7 natural, 16 synthetic, and 9 blended between natural and synthetic fibers, respectively. The dataset is divided into train and test datasets in three case ratios: 60:40, 70:30, and 80:20, utilized for both training to get hyperplane parameters and evaluating to measure the efficiency of the novel approach. The experimental result was found that the novel approach is robustness, and can generalize well to new data to achieve 100% accuracy in classifying the three groups of textile fibers with three case ratios. This method, which utilizes NIR sensors demonstrates rapid and reliable performance when compared with traditional methods using spectrometers or chemical analysis, could be crucial in optimizing the automation of textile recycling processes and promoting the transition to a circular textile economy.

1. INTRODUCTION

Textile fiber classification is a crucial role in the textile industry as it helps to inspect the composition of fibers during the production process, determine the quality and value of textile products [1], [2], and especially for identifying textile fibers and automatic sorting of textile waste in recycling process [3], [4], [5]. The textile factory is widely recognized as a waste pollution because of its textile production and post-consumer textile waste. The textile manufacturing process has significant environmental impacts, including the extensive use of non-renewable resources, making it the second highest user of land and the fourth highest user of water. It is also associated with high energy consumption, water pollution, and greenhouse gas emissions. According to estimates, the textile factory alone gives rise to approximately one and half a billion tons of carbon dioxide (CO_2) equivalent per year, which represents about 10% of the world's greenhouse gas emissions. Furthermore, it is responsible for 20% of the world's water pollution. In addition, textile waste with landfill is gotten rid of contributes to ocean pollution through microfibers [6], [7]. These factors clearly show that the textile factory provides a major effect on both environmental pollution and climate change.

Textile waste recycling is an essential solution to decrease the environmental effect on either the textile or fashion industry by reusing resources and minimizing waste disposal. However, global textile consumption has nearly doubled from 58 million to 109 million tons per year in the past decade, which has resulted in continuously rising post-consumer textile waste. Unfortunately, less than one percentage of the textile waste can be recycled into new clothes due to the limitations of recycling methods. The major challenge in textile recycling is not only the effective classification, but also the sorting technology of fiber component due to the property difference of synthetic fabrics made from polymer fibers and natural fabrics made from cellulose fibers, which require different reuse methods [8], [9]. Classification of textile fibers is difficult due to their complex structure, but NIR spectroscopy can be performed and has become a popular method for its convenience, efficiency, low cost, and efficacy to avoid time-consuming work when compared to traditional laboratory-based chemical analysis methods [10], [11], [12]. However, due to the huge amount of textile waste, it is need requires to develop the automated sorting system. To address this challenge, Du et al. [3] developed a classification and automatic sorting system using NIR devices (BIFT NIRMagic 6701), while Cura et al. [4] utilized NIR sensors (SIPTex) instead of traditional laboratory-based spectrometers. Both devices have been found to be efficient

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for identifying textile materials in automated sorting systems. These reasons clearly demonstrate the critical need to develop rapid and reliable methods for accurately identifying and separating textile materials using NIR sensors before the recycling process. This is essential to make textile recycling more efficient circular economy in textiles.

One of the main challenges in interpreting and efficiently classifying NIR data is its high dimensionality, complexity, wide variability, and strong correlation. Therefore, feature extraction or dimensionality reduction methods are necessary to eliminate redundant features or noise from the original spectra and create a new feature set that significantly improves classification accuracy. Reducing dimensionality in textile fiber classification widely applies Analysis of Principal Component (APC). Zhou et al. [1] applied PCA to reduce 601 variables in NIR spectra from the Brimrose Luminar 3060 AOTF-NIR to three Principal Components (PCs), which were used as input to SIMCA analysis, achieving 100% classification accuracy for seven types of fabric, grouped into three categories. Similarly, X. Sun et al. [12] utilized PCA to reduce 3,000 variables in NIR spectra from the Antaris II FT-NIR spectrometer to three PCs and used them as input for the ELM method, resulting in the recognition of all six fabrics with 100% accuracy.

In our previous study [13], we successfully classified natural fiber textiles using spectral data from the Neo-Spectra Micro sensor. Our research revealed that the signal enhancement in the proposed methods significantly improved the accuracy and precision of classification, increasing from 0.932±0.002 to 0.997±0.002 and from 0.773±0.004 to 1.000±0.000, respectively. To further improve the algorithm [14], we utilized matched filtering, a widely employed signal processing technique, to enhance the detection of specific pattern signals in the presence of noise. The primary goal of employing a matched filter is to maximize the SNR (the ratio of signal and noise), and facilitating both detection and extraction of the desired signals from background noise. The extracted features from the matched filter output, such as peak amplitudes, energy distributions, and other discriminative information, effectively represent the specific characteristics of each fiber group. Consequently, we developed two matched filter detectors from normalized reference spectra of natural and synthetic groups, enhanced by the l_2 norm. Our results demonstrate that the best overall accuracy for classifying textile fibers into three groups: natural, synthetic, and blended, was 0.9922±0.0078 with an 80:20 train-to-test ratio for original the dataset. In fact, the overall accuracy decreased slightly to 0.9899±0.0087 with a 60:40 train-to-test ratio, indicating the possibility of incorrect predictions, especially when tested on new, unseen data. Further exploration and refinement are required to enhance the generalization of our method for real-world applications.

This paper presents a novel method for textile fiber classification using NIR sensor data. The approach involves implementing two matched filters to enhance the detection of characteristic patterns found in both natural and synthetic fibers spectra. The output for the matched filter is then utilized to extract relevant features, which are subsequently used as input to create a three-class Support Vector Machine (SVM) model, which classifies into: natural, synthetic, and blended textile fibers. To evaluate classifiers performance, three evaluation metrics were used: overall accuracy, precision, and recall. The proposed method achieves 100% overall accuracy for three case of ratios of training and testing datasets, demonstrating its robustness and ability to generalize well to new data. In addition, the method requires less features for classification which reduces computation time and resource consumption. This makes it well-suited for use on embedded systems and has potential for real-world applications in automatic sorting of textile waste.

This paper is organized into five sections. The first section is an introduction. Section 2 describes the process of fabric sample preparation and NIR spectra collection used. Section 3 provides how to create the proposed approach including signal enhancement, matched filters, feature extraction and three-class SVM classification. Section 4 also shows performance results and its discussion. This paper are summaries, and recommended future work in section 5.

2. SAMPLE AND ACQUISITION

2.1. Sample preparation

The fabric samples used in this paper consisted of woven and knitted fabrics, which were obtained from fabric distributors and factories in Thailand and comprised various types commonly used in clothing production. To confirm the fiber composition of all fabric samples, we were sent to the Textile Testing Center, Thailand's Textile Institute (THTI), which that performs under the Foundation for Industrial Development (FID) of the Ministry of Industry. The fiber composition was determined based on the clean dry mass with percentage additions for moisture method under Thai Industrial Standard (TIS), Standards No.121 part 26-2552, which is a recognized method for identifying the quantity of binary mixtures of fibers in textile products.

The samples were categorized into three fiber groups based on their composition: natural fibers, synthetic fibers, and blended fibers. Samples containing cotton or rayon fibers were categorized as natural fibers, while samples containing polyester or spandex fibers were categorized as synthetic fibers. Samples with a mixture of cotton or rayon and polyester fibers were categorized as blended fibers. In total, there were seven, sixteen and nine fabric types of natural, synthetic, and blended fiber groups, respectively. Additionally, the blended fiber group were further divided into seven different ratios of natural to synthetic fiber: 68:32, 52:48, 48:52, 36:64, 35:65, 34:66 and 17:83. Therefore, there are ninety-six fabric specimens for training and testing the performance of the proposed method from thirty-two fabric types which have three distinct colors. The used dimensions for all fabric specimens were 30 centimeters by 50 centimeters.

2.2. Spectral Acquisition

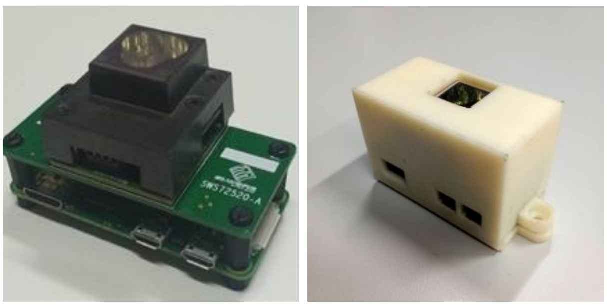
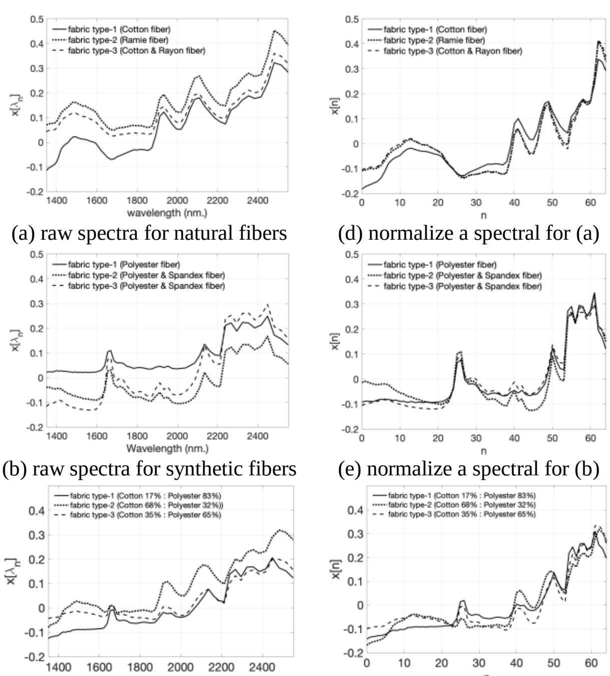


Fig. 1. The NeoSpectra Micro Development Kit and its housing for getting spectrum.

Previous studies have confirmed the potential of the NeoSpectra-Micro Development Kit as shown in the left side of Figure 1, is a portable NIR instrument as an easy, low-cost, reduced time-consuming and reliable device for analysis and classification in various fields, including food [15-17] healthcare [18], agriculture [19], and textile fibers [14].



(a) raw spectra for natural fibers (d) normalize a spectral for (a)

(b) raw spectra for synthetic fibers (e) normalize a spectral for (b)

(c) raw spectra for blended fibers (f) normalize a spectral for (c)

Fig. 2. Spectrum of fiber some samples $\{x[\lambda_n]\}$ in each group; normalized spectrum of fiber some samples $\{x[n]\}$.

We utilized the NeoSpectra-Micro Development Kit to scan all fabric specimens with a NIR wavelength from 1350 nm to 2500 nm by applying the Fourier transform infrared spectrometer. The sensor was connected and controlled by a Raspberry Pi computer board via serial peripheral interface (SPI), and all spectral data were stored in a CSV file for use in the proposed method. To avoid external light interference, the device was enclosed in a housing, as shown on the right of Figure 1.

The developed device generates each value of spectral signals in format of sixty-five pairs between absorbance and wavelength (λ_n) ranging from 1350 nm to 2550 nm, where n is negative integer between zero and sixty-four. A total of ninety-six fabric samples were measured at ten fixed locations to obtained 960 spectral specimen representing signals $\{x[\lambda_n]\}$ divided into 210 from 7 fabric types in natural fiber group, 480 from 16 fabric types in synthetic fiber group, and 270 from 9 fabric types in blended fiber group. Figure. 2 (a–c) show some fabrics samples from each fiber group with different fiber and fiber blend ratios.

3. PROPOSED METHODS

Figure. 3 shows the proposed method. The raw spectral data is divided into two datasets, and signal enhancement is performed before designing the matching filter. The resulting outputs are used to construct a three-class SVM classification model, and the performance of the novel approach is evaluated.

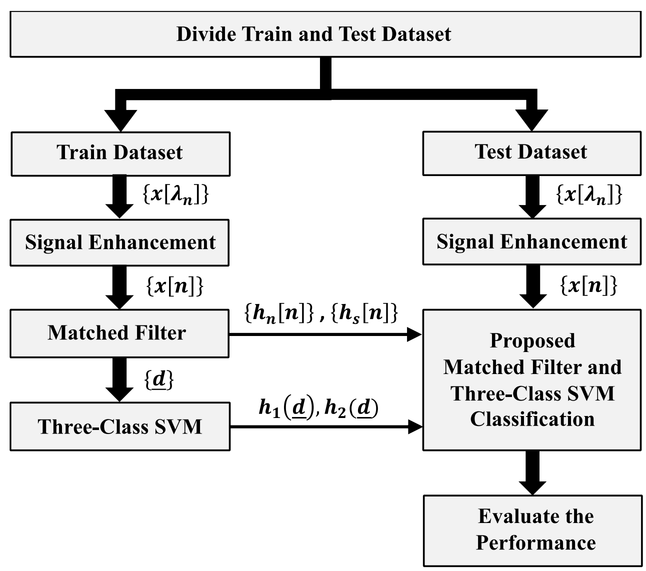


Fig. 3. Diagram of the novel method of novel textile fiber classification algorithm with matched filter and SVM.

Table 1: Number of Samples in each ratio

Ratio	Train dataset			Test dataset		
	Natural (N_n)	Synthetic (N_s)	Blended (N_b)	Natural (N_n)	Synthetic (N_s)	Blended (N_b)
60:40	126	288	162	84	192	108
70:30	147	336	189	63	144	81
80:20	168	384	216	42	96	54

3.1. Train and Test Datasets

To assess the accuracy of the proposed method, it is a common practice to divide all spectral signals samples $\{x[\lambda_n]\}$ of three types of fiber groups into two datasets: the train dataset and test datasets. Three ratios: 60:40, 70:30 and 80:20 as shown in Table 1 were also randomly used in this research.

3.2. Spectral Signal Improvement

To remove noise in input spectral signals $\{x[\lambda_n]\}$ for $n \in \{0, 1, 2, 3, \ldots, 64\}$ in a train dataset for each ratio, each input signal is normalized by its mean subtraction and its scalar division such that all signals have equal power to one, as shown in Figure 4.

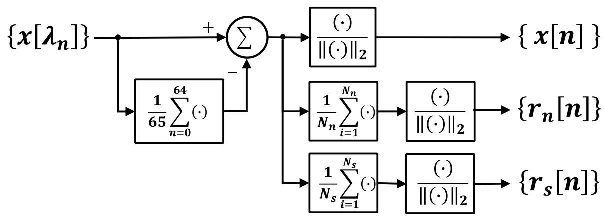
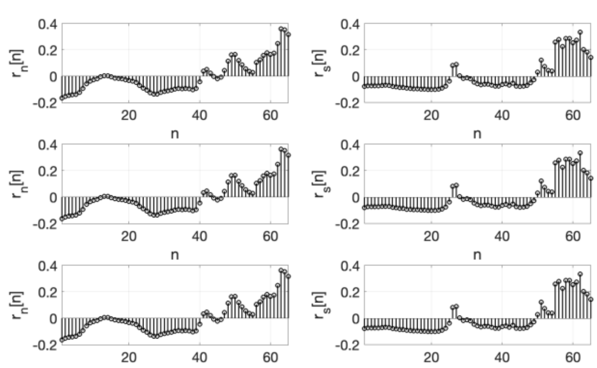


Fig. 4. Diagram of spectral signal enhancement and create a representative signal of natural and synthetic fibers.

3.3. Representative Signals for Natural and Synthetic

The proposed method involves developing two well-matched filters to detect characteristic patterns in the natural and synthetic fiber spectra. To achieve this, we generated representative signals for both groups, as shown in Figure 4. For the natural fiber group, we computed the mean of the spectral signal $\{x[\lambda_n]\}$ with reduced variability, where use spectral signals from the natural group (N_n samples) for each ratio in train dataset, and then divided the result by the l_2 norm of its signal to obtain a normalized representative signal $\{r_n[n]\}$ as shown in Figure 5(a).



(a) representative signal of the natural group

(b) representative signal of the synthetic group

Fig. 5. The representative signal of natural and synthetic for train to test ratio 60:40,70:30, 80:20, respectively.

In the similar fashion, a representative signal for synthetic $\{r_s[n]\}$ by used the spectral signal $\{x[\lambda_n]\}$ with reduced variability from the synthetic group (N_s samples) for each ratio in train dataset, as shown in Figure 5(b). The representative signals from various ratio in train data set exhibited very little variance, as evident from the figures. The mean standard deviation of the representative signals was 0.0004 and 0.0002 for natural and synthetic groups, respectively.

3.4. Matched Filter and Feature Extraction

After signal enhancement, the training datasets, including the normalized spectral signal $\{x[n]\}$ and the representative signals $\{r_n[n]\}$ and $\{r_s[n]\}$,were further normalized to have an equal power of one. These datasets were then utilized to create the matched filters in the proposed method.

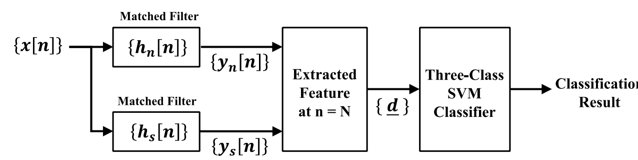


Fig. 6. The matched filter and three-class SVM for fiber classification.

The matched filters consist of two linear time-invariant (LTI) operators, where the desired filter is the reversed replica of the representative signals for natural fibers $\{h_n[n]\}$ and the other impulse response is the reversed replica of the representative signals for synthetic fibers $\{h_s[n]\}$, as governed by:

$$h_n[n] = r_n[65 - n]; \qquad n \in \{1,2,3, \ldots 65\} \qquad (1)$$

$$h_s[n] = r_s[65 - n]; \qquad n \in \{1,2,3, \ldots 65\} \qquad (2)$$

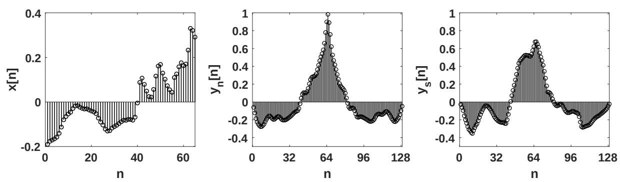
Figure. 6 shows the novel approach, where the input sequence $\{x[n]\}$ is apply to both matched filters $\{h_n[n]\}$ and $\{h_s[n]\}$ providing the two output sequences are specific by:

$$y_n[n] = h_n[n] * x[n]; \qquad n \in \{1,2,3, \ldots 65\} \qquad (3)$$

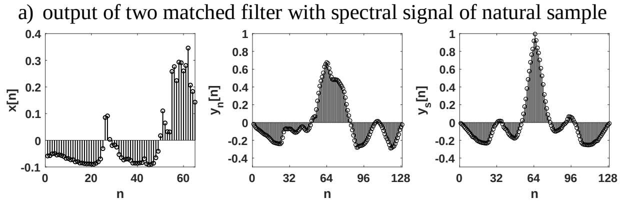
$$y_s[n] = h_s[n] * x[n]; \qquad n \in \{1,2,3, \ldots 65\} \qquad (4)$$

Next, through the comparison of the output of two matched filters using the normalized spectral signals $\{x[n]\}$ of natural, synthetic, and blended fiber spectra, respectively, as shown in Fig.7. We observed that the output values of $y_n[n]$ and $y_s[n]$at $n = 65$ from both matched filters enable efficient identification of fiber types based on their spectral characteristics. For example, in Fig. 7(a), when natural spectra signals are used as input, the impulse response of $y_n[n]$ almost the one, while the impulse response of $y_s[n]$ does not peak more than 0.7. Conversely, if the input is a synthetic spectra signal, the impulse response will give the opposite effect, as shown in Fig. 7(b). Furthermore, when the input is a blended spectra signal, both impulse responses will be above 0.7 but not peak nearly one, as shown in Fig. 7(c).

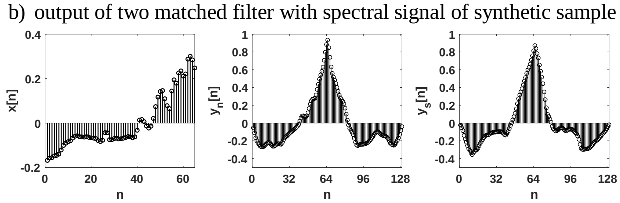
These output values denoted as y_n and y_s, respectively, represent extracted features from the original normalized spectral signals input $\{x[n]\}$. They effectively reduce the number of features from 65 to 2, enabling more efficient processing. These extracted feature vectors y_n and y_s, are then utilized to construct a new feature vectors $\underline{d}$, which serves as the input for creating the proposed three-class Support Vector Machine (SVM) model for textile fiber classification in the subsequent step.



a) output of two matched filter with spectral signal of natural sample



b) output of two matched filter with spectral signal of synthetic sample



c) output of two matched filter with spectral signal of blended sample

Fig. 7. Comparison of the output of each matched filters with input from each fiber type.

3.4 Three-Class SVM Technique

The machine learning technique developed by V. Vapnik [15] that is mainly used for binary classification tasks. Asually the machine learning is the SVM that can handle both linearly and non-linearly separable data by finding hyperplanes. They separate the data by the largest possible margin. In Figure 8, we can observe that the newly created feature vector $\{\underline{d}\}$ which consists of y_n and y_s, represent linearly separable for each fiber group. Therefore, a hard-margin SVM with linear constraints can be a suitable classification method [16]. The optimization problem for this type of SVM can be formulated as follows [17]

$$minimize\ \frac{1}{2}\ \|w\|^2 \tag{5}$$

$$subject\ to\ y\left(w^T\underline{d}\ + b\right) \geq 1$$

where, w is the weight vector that we want to learn; y is the label of train data set $y \in \{+1, -1\}$; $\underline{d}$ is a new feature vector of train data set; b is the bias term , $b \in R$.

To solve optimization problem in equation (5), we used the quadprog function in MATLAB, by transform it into a standard form. The parameters w and b are used to find the separating hyperplane and equation (6) represents the decision function of binary classification using a linear SVM classifier, where one class is for $h(\underline{d}) > 0$ and the another class is for $h(\underline{d}) < 0$.

$$h(\underline{d}) = sign(w^T\underline{d} + b) \tag{6}$$

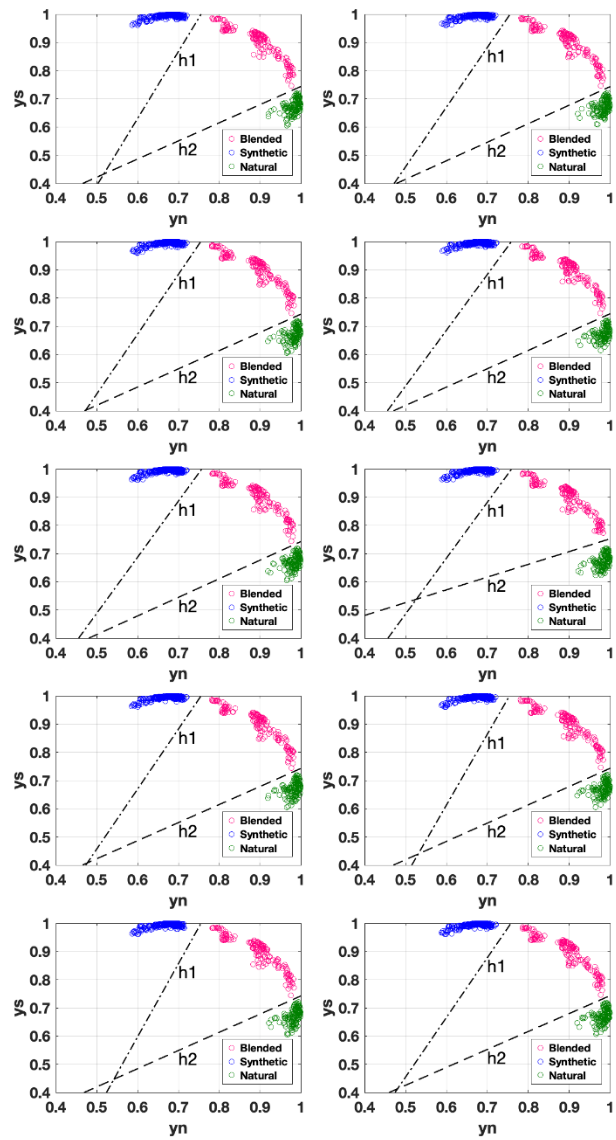


Fig. 8. The newly created feature vector from the proposed matched filter of the train: test Dataset (60:40).

Although Support Vector Machines (SVMs) are normally used for classification tasks into binary classes, by decomposing an M-class problem into the two-class problems, the SVM can be modified to multi-class scenarios. One-against-one is a common multi-class SVM method that creates M(M-1)/2 binary classifiers [18],[19] . This paper presented a novel approach to classify therefore, the three fibers groups: natural, blended, and synthetic. Traditionally, the one-against-one scenario would require creating three hyperplanes for each pairwise comparison. Therefore, we proposed using only two hyperplanes. The first hyperplane $h_1(\underline{d})$ is constructed with the synthetic area if

$h_1(\underline{d}) > 0$, and the blended area if $h_1(\underline{d}) < 0$. Conversely, the second hyperplane $h_2(\underline{d})$ is constructed with the blended area if $h_2(\underline{d}) > 0$ and the natural group if $h_2(\underline{d}) < 0$. Figure. 8 shows both hyperplanes using the train dataset and test datasets with a 60:40 ratio, randomly divided ten times. To obtain the average values of these parameters, ten times of random iterations were performed on various dataset ratios. The results of the parameters $\underline{w}_1$ and b_1 for building the hyperplane $h_1(\underline{d})$ are presented in Table 2, and the parameters $\underline{w}_2$ and b_2 for building the hyperplane $h_2(\underline{d})$ are presented in Table 3.

Table 2: SVM classifier of hyperplanes $h_1(\underline{d})$

Train: Test Ratio	$\underline{w}_1$		b_1
60:40	-29.6810	13.6521	8.8004
70:30	-30.1611	14.2165	8.6019
80:20	-29.9821	13.9054	8.7847
Mean	**-29.9414**	**13.9246**	**8.7290**
Std.	**0.2426**	**0.2827**	**0.1104**

Table 3: SVM classifier of hyperplanes $h_2(\underline{d})$

Train: Test Ratio	$\underline{w}_2$		b_2
60:40	-34.5351	54.4167	-5.9332
70:30	-33.5511	53.7046	-6.3976
80:20	-31.9360	52.5011	-7.1342
Mean	**-33.3407**	**53.5408**	**-6.4884**
Std.	**1.3123**	**0.9683**	**0.6056**

From Table 2 and Table 3, the standard deviation values of $\underline{w}_1$ and b_1 parameters of hyperplanes $h_1(\underline{d})$ are shown as 0.2426, 0.2827 and 0.1104, respectively. These values have very little variance, indicating that the size of the training and sampling data does not affect the process of finding the necessary parameters to generate the hyperplane for separating the Synthetic and Blended groups. On the other hand, the standard deviation values of $\underline{w}_2$ and b_2 parameters of hyperplanes $h_2(\underline{d})$ are shown as 1.3123, 0.9683 and 0.6056, respectively. These values have as slightly higher variance compared to $h_1(\underline{d})$. However, both hyperplanes generated from the newly extracted features of the matched filter output can still clearly separate the three groups of textile fibers, as evident from the figures in Fig. 8.

For classifying textile fibers into three groups with the two hyperplanes which we proposed is simplified approach aims to maintain high accuracy while reducing the computational complexity. The algorithm of the designed three-class SVM shown in Figure 9.

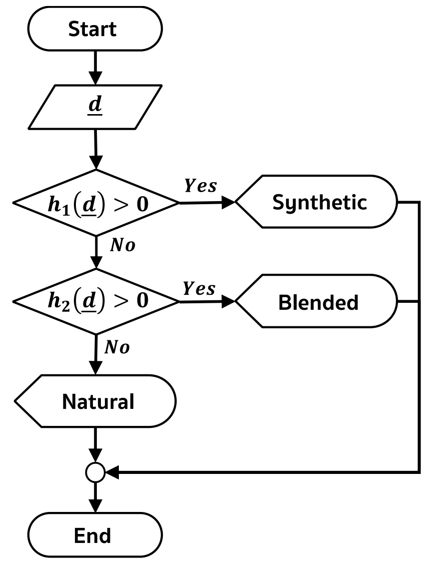


Fig. 9. The three-class SVM algorithm for textile fiber classification.

4. ANALYSIS OF PROPOSED METHOD PERFORMANCE AND EXPERIMENT RESULT

To evaluate our approach efficiency. Overall accuracy, Precision, and Recall are calculated by applying confusion matrix technique, as shown in Table 4. The prediction results are generated using a three-class SVM algorithm.

4.1. Confusion Matrix

Table 4: The confusion matrix to classify three classes

Classes	A_N	A_S	A_B
P_N	C_{11}	C_{12}	C_{13}
P_S	C_{21}	C_{22}	C_{23}
P_B	C_{31}	C_{32}	C_{33}

Table 4 shows a three classes confusion matrix, where A_N, A_S and A_B are actual class for natural textile fiber, actual class for synthetic textile fiber, and actual class for blended textile fiber, respectively. And P_N, P_S and P_B are predicted class for natural textile fiber, predicted class for synthetic textile fiber, and predicted class for blended textile fiber, respectively. Each value in the diagonal (C_{11}, C_{22} or C_{33}) correct classification of its class. Rest values of C_{21}, C_{31}, C_{12}, C_{32}, C_{13} and C_{23} represent number of false positive samples which are incorrect prediction (Tharwat, 2021).

4.2 The definition of Overall Accuracy

In order to measure Overall Accuracy efficiency to correct classification, the Overall Accuracy is used and specified by

$$Accuracy = \sum_{k=1}^{3} C_{kk} \Big/ \sum_{i=1}^{3}\sum_{j=1}^{3} C_{ij} \tag{7}$$

4.3 The definition of Precision Value

Precision value (PV) is the ratio of the number of each predicted class to the total number of three correct or incorrect actual class, and is specific by:

$$PV = \begin{cases} C_{11} \Big/ \sum_{k=1}^{3} C_{1k} & ,for\ predicted\ Natural\ Class \\ C_{22} \Big/ \sum_{k=1}^{3} C_{2k} & ,for\ predicted\ Synthetic\ Class \\ C_{33} \Big/ \sum_{k=1}^{3} C_{3k} & ,for\ predicted\ Blended\ Class \end{cases} \quad (8)$$

4.4 The definition of Recall Value

Recall value (RV) is the ratio of the number of each actual class to the total number of three correct or incorrect predicted class, and is specific by:

$$RV = \begin{cases} C_{11} \Big/ \sum_{k=1}^{3} C_{k1} & ,for\ actual\ Natural\ Class \\ C_{22} \Big/ \sum_{k=1}^{3} C_{k2} & ,for\ actual\ Synthetic\ Class \\ C_{33} \Big/ \sum_{k=1}^{3} C_{k3} & ,for\ actual\ Blended\ Class \end{cases} \quad (9)$$

To evaluate the proposed method's performance in classifying textile fibers into the natural, synthetic, and blended groups, we utilize the spectral signal input $\{x[\lambda_n]\}$ from the test dataset along with the parameters, i.e., $\{h_n[n]\}$, $\{h_s[n]\}$, $h_1(\underline{d})$ and $h_2(\underline{d})$ obtained from ten rounds (i) of random iterations with three ratios of a train to test data during the training process. The evaluation process consists of the following steps:

Step 1: Enhance the spectral signal input $\{x[\lambda_n]\}$ to obtain the normalized spectral signal $\{x[n]\}$.

Step 2: Extract features from the output of two matched filters $\{h_n[n]\}$ and $\{h_s[n]\}$, which were obtained from the training process at $n = 65$, resulting in a new feature vector $\{\underline{d}\}$.

Step 3: Utilize the newly feature vector $\{\underline{d}\}$ as input to classify textile fibers using the three-Class SVM algorithm with hyperplanes $h_1(\underline{d})$ and $h_2(\underline{d})$, which were obtained from the training process.

Step 4: Count and record the classification results in the format of the confusion matrix for three-class classification. Then, the overall accuracy, precision, and recall are calculated to evaluate the classification performance.

Table 5. Classification performance in case 60:40 ratio

Round *i*	Natural Class		Synthetic Class		Blended Class	
	PV	**RV**	**PV**	**RV**	**PV**	**RV**
I	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
II	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
III	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IV	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
V	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VI	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VIII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IX	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
X	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
$\boldsymbol{\mu}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
$\boldsymbol{\sigma}$	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

Table 6. Classification performance in case 70:30 ratio

Round *i*	Natural Class		Synthetic Class		Blended Class	
	PV	**RV**	**PV**	**RV**	**PV**	**RV**
I	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
II	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
III	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IV	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
V	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VI	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VIII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IX	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
X	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
$\boldsymbol{\mu}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
$\boldsymbol{\sigma}$	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

Table 7: Classification performance in case 80:20 ratio

Round *i*	Natural Class		Synthetic Class		Blended Class	
	PV	RV	PV	RV	PV	RV
I	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
II	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
III	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IV	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
V	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VI	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
VIII	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
IX	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
X	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
μ	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
σ	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

Table 8: Overall accuracy for fiber classification

Round *i*	Overall Accuracy		
	60:40	70:30	80:20
1	1.0000	1.0000	1.0000
2	1.0000	1.0000	1.0000
3	1.0000	1.0000	1.0000
4	1.0000	1.0000	1.0000
5	1.0000	1.0000	1.0000
6	1.0000	1.0000	1.0000
7	1.0000	1.0000	1.0000
8	1.0000	1.0000	1.0000
9	1.0000	1.0000	1.0000
10	1.0000	1.0000	1.0000
Mean	**1.0000**	**1.0000**	**1.0000**
Std.	**0.0000**	**0.0000**	**0.0000**

Tables 5 – 7 show that the proposed method has high precision and recall is 1.0 as well as high overall accuracy is 1.0 in all ratios of train and test data as shown in Table 8 It indicates that proposed method is performing extremely well in accurately identifying and classifying the data into their respective groups. This high level of performance suggests that the proposed technique is robust and can generalize well to new data. It also implies that the features used for training the three-class SVM classification are highly informative and relevant to the classification.

5. CONCLUSION

The paper presents the novel method classifying the fibers and applying NIR spectrum signals from NIR sensor. The proposed method uses two matched filters to create a new feature that is then used as input for training a three-class SVM classification. In Experimental result, the novel approach achieved an overall accuracy with 100% for three cases of ratios of train and test data indicating that it is robust and can generalize well to new data. Particularly in comparison to our previous study, the highest accuracy achieved is 0.9922±0.0078, exclusively with the use of an 80:20 training-to-test dataset. However, this accuracy decreases to 0.9899±0.0087 when tested under a 60:40 training-to-test dataset, further emphasizing the efficiency of the novel approach. Furthermore, the feature extraction vector used in this study is highly informative and relevant to the classification task. The findings of this study can be applied in various industries including fashion, textiles and materials science to get better accuracy and performance of the fiber classification in an automation process. In the future work, we improve to analytical methods in predicting the proportional of fiber composition either natural or synthetic in blended fabric.

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