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Forensic Characterization of Electrical Tapes Through Layer-Specific Analysis Using ATR-FTIR Spectroscopy and Chemometrics

التوصيف الجنائي للأشرطة الكهربائية من خلال التحليل الخاص بالطبقة باستخدام مطيافية الأشعة تحت الحمراء بتحويل فورييه مع توهين الانعكاس الكلي (ATR-FTIR) والكيمياء القياسية

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Abstract

Electrical tapes are frequently used by deviants and criminals to perpetrate violent crimes. These trace materials can be an ideal tool in solving such crimes. Although tapes can consist of multiple layers, their characteristics and primary functions are largely determined by the adhesive and backing layers. In the present study, a total of 25 electrical tapes from different manufacturers were analyzed for both the backing and adhesive sides using a non-invasive, non-destructive analytical technique, ATR-FTIR. The spectral data revealed presence of rubber-based and acrylic-based adhesives with rubber-based adhesives being more common while PVC as the primary backing material. Further chemometric classification using Principal Components (PCs) based Discriminant Analysis (DA) attained an original and cross-validated accuracy of 100% in classification of adhesives and 100% original and 88% cross-validated accuracy in classification of backing. Alternatively, the SVM model demonstrated strong potential as a chemometric classifier, achieving up to 100% accuracy in distinguishing adhesives and backings of electrical tapes, with cross-validation accuracies of 100% for the adhesive side and 92% for the backing side, respectively. Study reveals ATR-FTIR as a valuable analytical tool for preliminary identification of chemical

Keywords: forensic sciences, electrical tapes, IR spectroscopy, chemometrics, classification, SVM

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المستخلص

غالبًا ما يستخدم المنحرفون والمجرمون الأشرطة الكهربائية في ارتكاب الجرائم العنيفة. ويمكن اعتبار هذه الأدلة الأثرية (المواد النزرة) أداة مثالية للمساعدة في حل مثل هذه الجرائم. وعلى الرغم من أن الأشرطة قد تتكون من طبقات متعددة، فإن خصائصها ووظائفها الأساسية تتحدد إلى حد كبير بالطبقتين اللاصقة (Adhesive) والدعامة (Backing).

في الدراسة الحالية، تم تحليل ما مجموعه 25 شريطًا كهربائيًا من جهات تصنيع مختلفة لكل من جانبي الدعامة والمادة اللاصقة، وذلك باستخدام تقنية تحليلية غير جائرة وغير تدميرية، وهي مطيافية ATR-FTIR.

كشفت البيانات الطيفية عن وجود مواد لاصقة قائمة على المطاط وأخرى قائمة على الأكريليك، وكانت المواد اللاصقة القائمة على المطاط هي الأكثر شيوعًا، بينما كان البولي فينيل كلورايد (PVC) هو المادة الأساسية للدعامة.

علاوة على ذلك، حقق تصنيف القياسات الكيميائية باستخدام التحليل التمييزي (DA) القائم على المكونات الرئيسية (PCs) دقة تصنيف أصلية ومدققة متقاطعًا بلغت 100% في تصنيف المواد اللاصقة، و 100% (أصلية) و 88% (مدققة متقاطعًا) في تصنيف طبقة الدعامة.

وبدلاً من ذلك، أظهر نموذج آلة المتجهات الداعمة (SVM) إمكانات قوية كمصنف كيميائي إحصائي، حيث حقق دقة تصل إلى 100% في التمييز بين المواد اللاصقة وطبقات الدعامة للأشرطة الكهربائية، مع دقة تحقق متقاطع بلغت 100% للجانب اللاصق و 92% لجانب الدعامة، على التوالي.

الكلمات المفتاحية: علوم الأدلة الجنائية، الأشرطة الكهربائية، مطيافية الأشعة تحت الحمراء (IR)، الكيمياء القياسية(Chemometrics)، التصنيف، آلات المتجهات الداعمة (SVM)

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constituents of the electrical tapes and with chemometric models like DA and SVM, it could successfully link adhesives and backings to their respective groups. SVM models which haven't been used much in previous studies, appeared to perform better than traditional chemometric models in the current study.

تُظهر الدراسة أن تقنية ATR-FTIR هي أداة تحليلية قيمة لتحديد المكونات الكيميائية الأولية للأشرطة الكهربائية، وأنه باستخدام النماذج الإحصائية الكيميائية مثل DA و SVM، يمكن ربط المواد اللاصقة وطبقات الدعامة بنجاح بمجموعاتها الخاصة. وظهر أن نماذج SVM، التي لم تُستخدم كثيرًا في الدراسات السابقة، تفوقت في الأداء على نماذج القياسات الكيميائية التقليدية في الدراسة الحالية».

1. Introduction

Electrical tapes, also referred to as insulating tapes or vinyl tapes are commonly encountered at crime scenes and submitted to laboratories for examination, often as exhibits associated with explosions, burglary, theft, arson and smuggling of contrabands [1]. Comparative analysis of electrical tape samples mainly allows for exclusion, whilst in rare cases can also link questioned tape fragments to its source [2].

Electrical tapes like other pressure sensitive adhesive tapes are composed of multiple layers, wrought by means of a sequence of milling and mixing processes which ultimately results with the melding of these layers through the coating and calendaring process. The two predominant layers however, in the electrical tapes are adhesive and backing [3]. The electrical tapes typically encompass a pressure sensitive adhesive layer backed on flexible polyvinyl chloride (PVC) carrier which adheres to most surfaces with application of light pressure [4]. The pressure sensitive adhesives retain their tackiness throughout, and consists of multiple components such as elastomers, tackifying resins, plasticizers, fillers, stabilizers, release coatings and flame retardants. Elastomers play a crucial role in determining the physical and chemical characteristics of adhesives, with rubber-based (polyisoprene, polyisobutylene, styrene/isoprene copolymer, styrene/butadiene copolymer) and acrylic-based types being the most widely used in electrical tapes [1]. Backings are flat, pliable materials to which adhesive layers are applied and is typically polyvinyl chloride in electrical tapes. However, several studies have reported use of other types of backing material such as polyester, polyimide, polyethylene and butyl rubber [5]. The backings further comprise plasticizers, stabilizers, colorants, flame retardants, opacifiers and fillers for desired properties, price and purpose [6-8]. The electrical tapes are available in wide variety of colours; however, the most common colour is black.

The electrical tapes available in the markets vary in their chemical composition and manufacturing process making it possible to individualize and identify them, adding to their potential value as evidence.

The forensic analysis of electrical tapes initiates with physical matching, followed by comparison of physical characteristics such as dimensional features, microscopic characteristics, fluorescence etc. While matching of fragment ends can be conclusive in sourcing tape fragments to known roll specimen, is not very reliable as is flexible and get stretched when torn [9]. So, regardless of the physical match, analytical examination proceeds. As per the ASTM E3260-21 protocol for forensic examination of pressure sensitive adhesive tapes, analytical techniques utilized for their examination include but is not limited to polarized light microscopy (PLM), vibrational spectroscopy (IR & Raman spectroscopy), chromatographic technique (Pyrolysis Gas Chromatography – Mass Spectroscopy), elemental analysis techniques (SEM-EDX, XRF, ICP-MS) and X-ray Diffraction [10].

IR spectroscopy is one of the first analytical technique employed in the examination of electrical tapes owing to its simplicity, cost-effectiveness and utility, and is the easiest way to link a tape to the supplier [11]. Advent of modern FTIR (Fourier Transform Infrared) instruments with incorporation of ATR (Attenuated Total Reflectance), allows for rapid, non-invasive, non-destructive examination of these with little to none sample preparation [12]. It is particularly relevant in delineating information about polymeric constituents of the tapes. The both layers of the electrical tapes are multi-component formulations in which inherent constituents are mixed in varying proportions, often specific to the manufacturers. The variability in the composition yields infrared spectra of adhesives and backing that are readily distinguishable and classifiable [1][5]. Kee (1984), in his study on the backing of PVC electrical tapes, employed IR spectroscopy to further classify the backings initially categorized using XRF [13]. Similarly, Keto (1984) utilized IR spectroscopy for examining the adhesives of black electrical tapes [14]. Both studies highlighted the significant utility of FTIR in distinguishing and classifying tapes from different manufacturers. Merrill and Bartick (1992) reported that IR analysis of adhesives provided greater discrimination of tape samples compared to the backing, a finding later corroborated by Goodpaster et al. (2009) [15][16]. Mehltretter et al. (2011) classified adhesives of 90 electrical tapes using FTIR into 8 groups with a discrimination of 67%. Three of these adhesive groups were polyisoprene based, three were acrylic based, one was butadiene based and one was not easily interpreted. Majority of the tapes analysed were identified as isoprene based [1]. Similar study on backing of same 90 electrical tape samples by Mehltretter et al. (2011) classified backings into 14 groups using FTIR, majority of which were PVC based [5]. Zięba-Palus (2017), further using ATR-FTIR, classified the adhesives and backings of PSA tapes (electrical, packaging, and duct tapes) into four groups. The adhesives identified included natural isoprene rubber, styrene–butadiene rubber, esters, and acrylates, while the backings were composed of polypropylene, polyethylene, polyester, and acetylated cellulose [17]. Nimi et al. (2022) demonstrated the effectiveness of ATR-FTIR in classification of adhesive and backing layers of electrical tapes using chemometrics [18]. These studies show practical utility of FTIR in preliminary classification of electrical tapes and distinguishing between them through a non-destructive and non-invasive approach.

The present study focuses on identifying the polymeric constituents of the adhesives and backings of electrical tapes from 25 different manufacturers available in the Indian market using FTIR, followed by chemometric classification through Principal Component Analysis (PCA) and Principal Components (PCs)-based Discriminant Analysis (DA). While PCA and DA have been widely applied in chemometric classification of trace evidences, other machine learning techniques have not been explored extensively. Prior applications of Support Vector Machine (SVM) in trace evidence analysis have largely been limited to geo-forensics and soil provenance, classification of body fluids, and identification of accelerants in arson exhibits [19]. Addressing this gap, the current study assesses the potential of SVM as an alternative to traditional chemometric techniques for classification of electrical tapes.

2. MATERIALS AND METHODS

2. 1. Sample Collection

The present study was carried on electrical tapes of 25 different brands collected from the local market of the Jhansi region of India and e-shopping websites (amazon.in, flipkart.com) covering most

Table 1. *Sample Description and Sample Codes used in the Study*

S. No.	Sample Code	Sample Name	Colour	Manufacturer/Marketed by
1.	RSE1	Gegrip	Black	Parsvnath enterprises, India
2.	RSE2	KCU Hans	Black	Kyasha Industries, India
3.	RSE3	ETI	Black	Essence Tape Industries, India
4.	RSE4	E-Fab Supreme	Black	Takeway Retails, India
5.	RSE5	Steelgrip + Pidilite	Black	Deon Tape Industries, Pidilite Industries Limited, India
6.	RSE6	Wonder Espark	Black	Wonder Espark, India
7.	RSE7	ATGRIP +	Black	Attrio Technologies, Haryana, India
8.	RSE8	Goldmedal	Black	Gomec Industries, Mumbai, India
9.	RSE9	3M Super 33+	Black	3M Electro & Communication, Puducherry, India
10.	RSE10	Cosmo Strong Grip	Black	Maxmon, New Delhi, India
11.	RSE11	Aston	Black	Aston Packaging Solutions, Chennai, India
12.	RSE12	Sona	Black	Sona Electrosolutions, India
13.	RSE13	Astral Resitape	Black	Astral, Kanpur, India
14.	RSE14	Euro	Black	Euro Tapes, Delhi, India
15.	RSE15	Invoke	Black	Shiva Industries, Delhi, India
16.	RSE16	Gomec	Black	Gomec Industries, Mumbai, India
17.	RSE17	Care n touch	Black	Care n touch, India
18.	RSE18	Glue King	Black	Glue King Impex, India
19.	RSE19	JQL Jindal Quality Tapes	Black	JR Jindal Infraprojects Pvt. Ltd. Delhi
20.	RSE20	Trendicraft Electrical Tapes	Black	Ecommasters, Trendicraft Store, India
21.	RSE21	Prochem	Black	Holy Faith Enterprises, India
22.	RSE22	EZWonder	Black	Ezwonder, India
23.	RSE23	Biocon	Black	Biocon Electric Pvt. Ltd., India
24.	RSE24	Electronics Spices	Black	Risabh Trading, India
25.	RSE25	iSTIX Wonder	Black	Instabiz Solutions India Pvt. Ltd., India

of the available prominent brands in household applications in the region. All the tapes used for the study were black in colour owing to its commonness in application. Table 1 enlists the tapes from different manufacturers used in the study along with their respective sample codes. All the samples were stored in uniform condition prior to analysis. The samples were analyzed directly in their pristine form using ATR-FTIR. A piece of tape of dimension 1x1 cm^2 was cut with scissor and placed directly on the stage with side to be analyzed facing the crystal to collect the spectral information. The pressure anvil was tightened to maintain optimum contact between the sample and the crystal. The samples were analyzed uniformly under consistent instrumental and environmental parameters with prior background scanning before each sample. Additional replicate spectrum of each sample was collected to assess reproducibility qualitatively. The spectra were further compared with available pre-published literature (Mehltretter et al., 2011; Mehltretter et al., 2011; Smith, 2007; Nimi et al., 2021) to assess if they follow the generalized spectral appearance mentioned there or not [1, 5, 9, 18].

2. 2. Instrumentation and Analytical Parameters

All the samples (RSE1-25) were analyzed using PerkinElmer Spectrum IR (Instrument Model: Spectrum 2) with MIR TGS (tri glycine sulphate) detector and equipped with universal ATR (diamond crystal), available at Innovation Centre, Bundelkhand University, Jhansi. The samples were scanned in the mid IR range of 4000-400 cm^{-1} with spatial resolution of 4 cm^{-1} and 64 co-added scans. The spectra were collected in transmittance mode using NIOS2 software. The ATR crystal was cleaned prior to- and after each spectral analysis with spectroscopic grade Isopropanol and lint-free tissue paper. All the samples were analyzed in a continuous manner with background/blank scan for air or other environmental factors preceding the analysis of each sample with same conditions as used for sample analysis. The adhesives and backings were analyzed by placing the adhesive sides and backing sides of tape facing the crystal respectively and applying a contact force of 70 N (as specified by manufacturer/centre in their SOP for most analysis).

2. 3. Chemometrics

Chemometrics is defined as application of mathematics and statistics to solve research problems in analytical chemistry [20]. Chemometric methods allow for identification of intricate patterns within the vast amount of analytical data and provides for objective interpretation. The present study used Principal Components Analysis (PCA) for dimensionality reduction and cluster visualization. The Principal Components (PCs) were further used as independent variables in discriminant analysis (DA) for supervised classification. While for backing sides, clustering was done by Wards' method using squared Euclidean distance as visual classification of spectra was not possible. The clusters were used to assign classes to backing samples which were further assessed by principal components-based discriminant analysis model. An alternate supervised classification technique SVM was also used for classification of adhesives and backing sides in their respective groups. All the statistical analyses were performed using The Unscrambler X 10.4 (64 bit).

2. 4. Data Pre-processing

Prior to chemometric analysis, FTIR spectra were subjected to the following preprocessing pipeline:

1. Removal of saturated/noisy edges: Spectra were trimmed 3700–600 cm^{-1} to remove high-wavenumber instrument noise and low-wavenumber diamond/ATR artifacts.
2. Atmospheric correction: Exclusion of atmospheric CO_2 region (2400-2251 cm^{-1}).
3. Smoothing + derivative: Savitzy-Golay filter was employed to smoothen the spectra and compute the first derivative (window = 11 points, polynomial order: quadratic, derivative order = 1).
4. ATR Correction: The data was further subjected to basic ATR correction with reference peak 1000 cm^{-1} which is commonly

used for polymers and organic samples, including adhesives.

5. Normalization: ATR corrected data was normalized using SNV (Standard Normal Variate) followed by unit vector normalization (L2) to remove pathlength differences.

All data preprocessing was carried out using The Unscrambler X 10.4 (64-bit) software, and both the raw and processed datasets are accessible via the following DOI: 10.5281/zenodo.17495976.

2. 5. Principal Components Analysis (PCA)

Principal Components Analysis (PCA) is a multivariate statistical technique for reducing dimensions of a dataset with large number of correlated variables. The technique identifies principal components (PCs) which are linear combinations of original variables. These components are not correlated unlike the variables and are at right angle to each other [20]. The first principal component usually accounts for the maximum explained variance followed by the others [21]. In the present study PCA was used as preliminary stage of data preprocessing and cluster visualization, so that the scores can further be used as variables for discriminant analysis. Prior to PC computation, mean normalization was performed to ensure PCA analyzes the variation around the mean rather than the absolute values. The study used SVD (singular vector decomposition) PCA with cross-validation identifying principal components and determining PC scores using Unscrambler statistical software. The number of PCs to be used for further classification and characterization was determined by scree plot and eigenvalues. Outlier analysis was performed using F-residuals and leverage-type Hotelling T^2, with the warning height (WH) and alpha height (AH) set to 1% and 0.1%, respectively.

2. 6. Discriminant Analysis (DA)

Discriminant Analysis (DA) also referred as Discriminant Function Analysis (DFA) is a common multivariate statistical technique often used for supervised pattern recognition [19]. Discriminant analysis initially creates a discriminant function which is linear combination of original variables. The objects within the same groups have similar discriminant scores [20]. The present study used PC-based discriminant function analysis for classification and validation of the groups of the adhesives and the backing of electrical tapes. The viability of model was assessed by wilks' lambda, F-value, eigenvalues and their corresponding significance. The current study used leave-one-out cross-validation (LOOCV) for cross-validation. All the statistical parameters were calculated at 95% confidence interval.

2. 7. Support Vector Machine (SVM)

Support vector machine is another supervised pattern recognition algorithm, gaining popularity as machine learning technique for both classification and regression. However, it hasn't been exploited much as chemometric technique but holds a great potential as it is capable of classification even with relatively smaller datasets [19]. The technique classifies objects by recognizing decision boundary which most effectively separates the data. The points that are nearest to the hyperplane and define its boundary are referred to as support vectors [22]. The current study employed C-SVC (C-Support Vector Classification) type SVM with C value calculated by grid search. The study used radial and linear kernels for classification of adhesives and backings respectively with k-fold cross-validation. The 10-fold cross-validation was chosen to avoid overfitting as sample size was small and limited.

3. RESULTS

The spectral data of the adhesive and backing sides of the electrical tapes were manually compared to reported findings and IR databases followed by chemometric analysis as discussed in subsequent sections.

3. 1. Adhesives

Spectral Findings

The spectral findings demonstrate aliphatic hydrocarbon as fundamental polymeric backbone for elastomers in the adhesives across all the 25 samples (RSE1-RSE25) with prominent absorption bands in C-H stretching region, typically appearing around 3000-2800 cm^{-1}. The samples almost consistently showed peaks at ~2956 cm^{-1} and ~2925–2915 cm^{-1} corresponding to asymmetric CH_3 and CH_2 stretching respectively and peak corresponding to CH_2 symmetric stretching at 2870-2850 cm^{-1}. This along with characteristics bands at 1450 cm^{-1} and 1376 cm^{-1} attributable to CH_2 scissoring and symmetric CH_3 bending further underscore the presence of predominant aliphatic backbone, more likely rubber or acrylics [9, 23]. All the samples display a strong absorption band at ~1730 cm^{-1} characteristic of carbonyl (C=O) stretching suggesting presence of esters which may be due to ester plasticizers, rosin ester tackifiers or from acrylics. Furthermore, peaks in the range 1600-1580 cm^{-1} from C=C stretching and at ~700cm^{-1} corresponding to C-H deformation suggests the presence of aromatic components such as styrene [24-25]. The spectral comparison revealed two major groups of adhesives present in the electrical tapes used in the current study.

Group A (RSE1-8, RSE10-11, RSE14-16, RSE18-22 and RSE 25) showed presence of rubber-based adhesives, typically synthetic rubbers (styrene butadiene rubber or styrene isoprene copolymer) with major peaks in C-H stretching region, prominent CH_2/CH_3 deformations and distinct C=C peaks. The group additionally showed a strong, sharp carbonyl absorption characteristic of esters at 1728 cm^{-1} and 1270 cm^{-1}. The peak at 1450 cm^{-1}, 1376 cm^{-1} and 966 cm^{-1} can be indicative of tackifying resins. Further, a peak at 966 cm^{-1} could also be attributed to butadiene 1, 18, 26].

Group B (RSE12-13, RSE17, RSE23-24) exhibited presence of acrylic-based adhesives. While, the group B samples showcased a similar spectrum with major peaks in 3000-2800 cm^{-1} (C-H stretching), at ~1728 cm^{-1} (-C=O stretching), ~1450 cm^{-1} (CH_3 deformation), ~1377 cm^{-1} (CH_2 deformation), 1270-1240 cm^{-1} (-C-O-C asymmetrical stretching), 1162 cm^{-1} (-C-O-C symmetrical stretching). Further, peaks at 1064 cm^{-1}, 1022 cm^{-1} and 741 cm^{-1} are all consistent with the acrylates [23, 27]. While, spectral patterns of the sample in group B are broadly similar, it doesn't show an almost complete overlap as spectra of samples in group A. Sample RSE17 and RSE23 seemingly appeared more similar while RSE12 and RSE24 were found to be more closely associated. RSE 13 was found to be relatively more similar to the former.

Spectrum of RSE9 however differed significantly from all the other samples showing significantly higher absorption as compared to the other groups as shown in the representative Figure 1 (Representative spectra of rubber-based adhesive (RSE1), acrylic-based adhesive (RSE12) an RSE9). Nonetheless, packaging of the tape mentioned presence of rubber-based adhesives as constituent and spectral data also revealed characteristic peaks of rubber-based adhesives with higher absorption, along with numerous peaks which were not present in any of the above groups indicating a different chemical formulation.

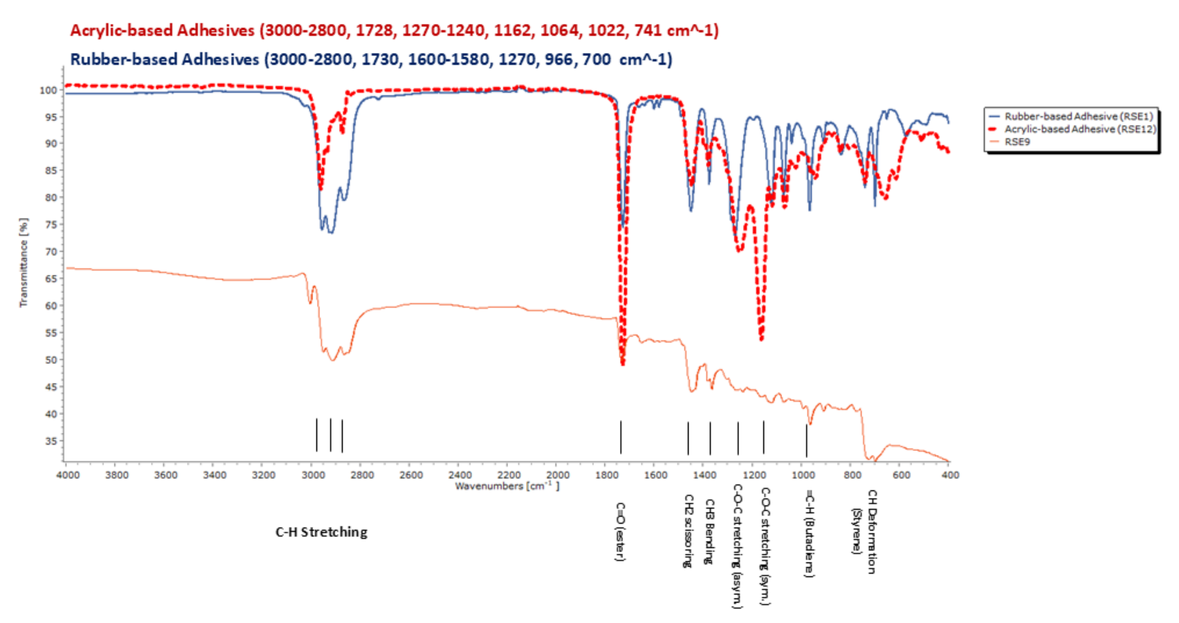

Figure 1- *Representative Spectra of Rubber and Acrylic Adhesives with Band Assignments (RSE 1, RSE12 & RSE9)*

3. 2. Chemometric Analysis

Principal Components Analysis (PCA)

The spectral data of the adhesive side for all the samples was subjected to chemometric analysis using unsupervised learning method viz. PCA for dimensional reduction and cluster observation. A total of ten PCs were initially computed for the processed data. First eight PCs explained more than 99% of the total variance of the dataset with first PC accounting for 55% of variance followed by PC2 (25%), PC3(13%), PC4(2%), PC5(2%), PC6(1%), PC7(1%) and PC8(1%). The explained variance is shown in scree plot (Figure 2). The two-dimensional scatter plot between PC1 and PC2 visualizes rubber-based adhesives as a close cluster which is also obvious from the spectral interpretation. However, acrylic-based adhesives unlike rubber-based adhesives didn't form a close cluster indicating a significantly varying chemical constitution even though elastomeric backbone is identical. RSE9 appeared completely isolated from other samples further corroborating a markedly distinct chemical composition from Group A and B as underscored in the spectral findings.

The score plot (Figure 3) further depicts most samples in group A to be having positive PC-1 values and negative PC-2 values barring RSE11 and RSE19 which though show positive PC-2 value but are still close to zero. Acrylic-based adhesives showed negative values for both PC-1 and PC-2. RSE9 demonstrated negative value for PC-1 while positive value for PC-2. According to the PCA results, sample RSE9 was flagged as a Hotelling T^2 outlier in the second principal component (PC-2) of the current model and was thus not included for further supervised classification models.

As the scatter plot between PC1 and PC2 reveals the correlation of rubber-based adhesives and acrylic-based adhesives with the principal components, combined loading plot (figure 4) of PC1, PC2 and PC3 further reveals the correlation between PCs and wavenumbers. PC1 exhibits pronounced positive loadings for ester functional groups, characterized by sharp peaks near 1735 cm^{-1} and strong C–O stretching bands around

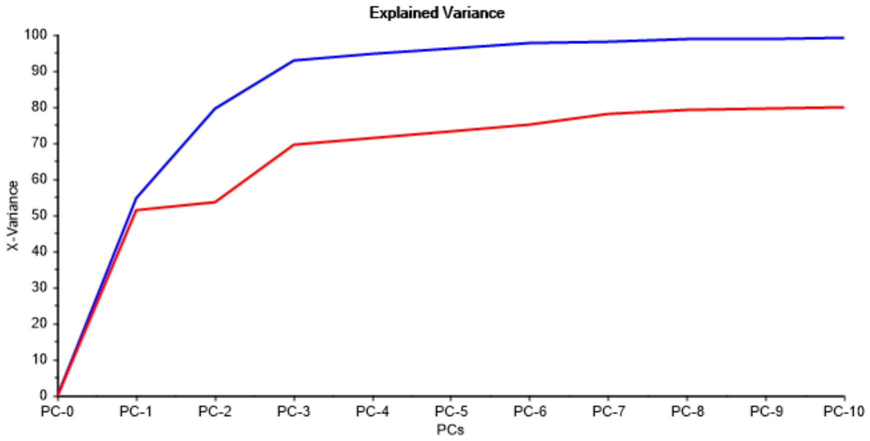

Figure 2- *Scree Plot along with Cross-validation for Adhesives Spectra*

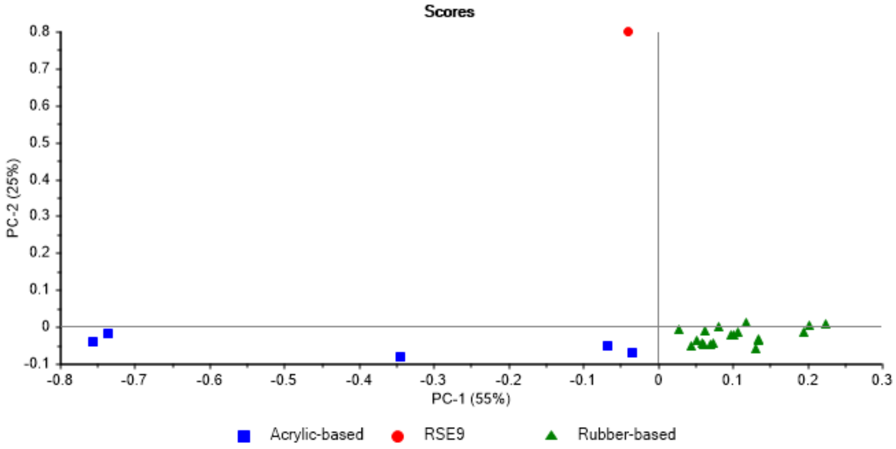

Figure 3- *Score Plot PC1 v. PC2 for Adhesives*

1240 cm^{-1} and 1165 cm^{-1}, while showing negative loadings for C–H stretching vibrations of CH$_2$/CH$_3$ groups at approximately 2920 cm^{-1} and 2850 cm^{-1}. Additional negative contributions at 1460 cm^{-1} and 1375 cm^{-1} correspond to C–H bending modes. Overall, PC1 captures the primary chemical differentiation between rubber-based and acrylic-based adhesives. PC2 also demonstrates strong associations in the regions related to C–H stretching, ester linkages, and the 1450–1200 cm^{-1} range, but exhibits opposite polarity to PC1 for certain bands, indicating that it reflects secondary compositional variations, likely arising from differences in tackifier or plasticizer content. PC3 shows relatively low-amplitude variations, with correlations near 2950–2800 cm^{-1} and 1100–900 cm^{-1}, regions typically attributed to minor components such as fillers, oxidation by-products, or additives.

3. 3. Discriminant Function Analysis (DFA)

The classification between rubber-based and acrylic-based adhesives was further assessed by PC based discriminant function analysis model. Based on the Scree plot, first eight PCs explaining almost 100% of the variance of dataset were utilized for building this model. Test of equality of group means revealed PC1 to be most significantly contributing to the discrimination with wilk's lambda and F-value of .362 and 38.760 respectively (sig. <.001) followed by PC2 with wilks' lambda and F-value of .820 and

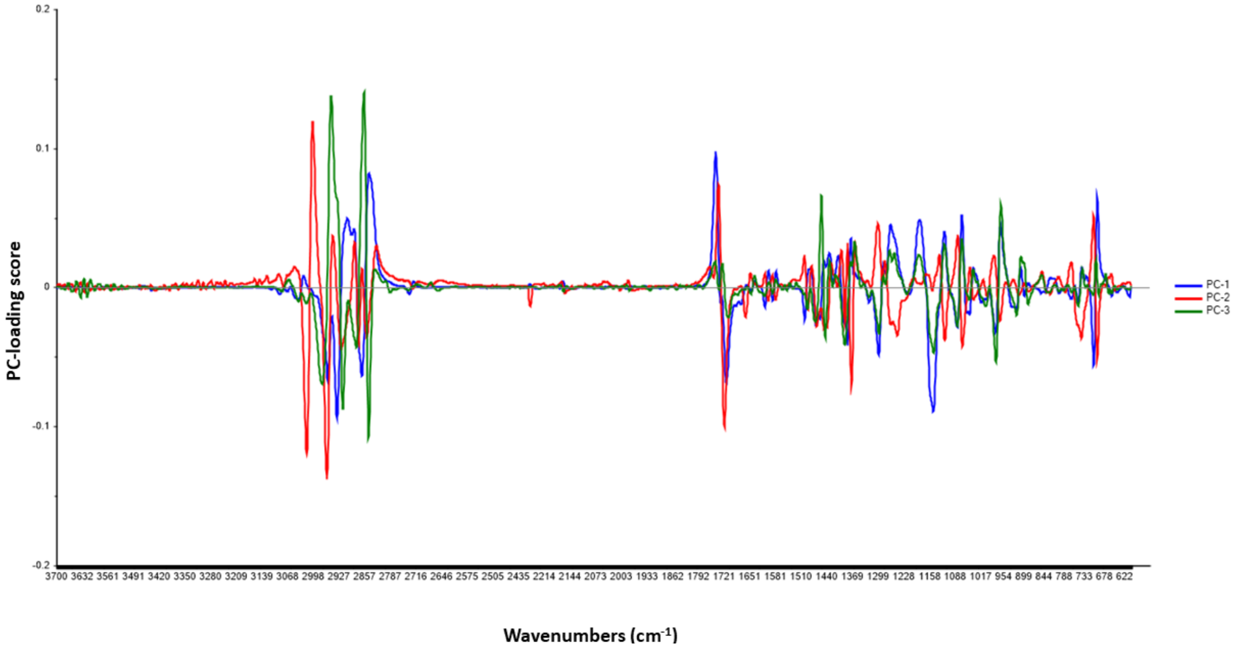

Figure 4- *Combined Loading Plot of PC1, PC2 and PC3 for Adhesives*

Table 2- *Summary of Discriminant Function Model for Adhesives Classification*

VARIABLES	RAW COEFFICIENT	CONSTANT	GROUP CENTROID		ACCURACY		Wilk's Lambda
			Rubber-based	Acrylic-based	O[1]	CV[2]	
PC1	-14.189	2.283	-1.908	7.250	100	100	.062
PC2	65.847						(Sig. <.001)
PC3	-1.858						
PC4	43.531						
PC5	-44.234						
PC6	-9.444						
PC7	22.669						
PC8	51.734						

1: Original accuracy, 2: Cross-validated accuracy.

4.831 respectively (sig. <.05). The other PCs didn't contribute significantly to the discriminant function model as depicted by high wilk's lambda value and typically lower F-values. Typically, in discriminant models, wilks' lambda value closer to zero and higher F-value suggests greater discrimination. The model yielded a canonical discrimination function with eigenvalue of 15.090 with canonical correlation of .968 covering cumulative variance of 100%. The summary of the discriminant function model is shown in table 2.

The model achieved an original and cross-validated accuracy of 100%. All the twenty-four samples containing 19 rubber-based adhesives and 5 acrylic-based adhesives used in the classification model were correctly classified to their respective groups.

Table 3- *Summary of Performance of Support Vector Machine Model for Classification of Adhesive Layers*

Identified Support Vectors	Coefficients
RSE2	1.0960
RSE4	0.1429
RSE11	0.6541
RSE22	1.7375
RSE25	2.3179
RSE12	-0.5484
RSE23	-4.8867
RSE24	-0.5135

Confusion Matrix

→ Actual ↓ Predicted	Group A	Group B
Group A	19	0
Group B	0	5

Group wise Accuracy

Group A: 100%

Group B: 100%

Overall Accuracy: 100%

Validation Accuracy: 100%

Probabilities

Probabilities	AxB
Rho	0.0098
ProbA	-2.4402
ProbB	-0.3738

SVM Parameters

SVM type: Classification (C-SVC)
Kernel type: Radial basis function
Gamma: 10
C value: 10
Cross validation segments: 10

3. 4. Support Vector Machine (SVM)

The spectral data of adhesives were further assessed by alternate supervised classification method viz. support vector machine. The eight PCs, initially employed for DFA were further used as the variable for the SVM model built in the present study. The current study used C-SVC (C-Support Vector Classification) type of SVM and radial kernel. The optimal SVM parameters were determined through a grid search, wherein the C parameter and γ (gamma) were both set to 10. The grid search was conducted within the range $\log_{10}(\gamma)$: –2 to 2 and $\log_{10}(C)$: –2 to 2, each evaluated at five levels. Model performance was assessed using automated 10-fold cross-validation to ensure generalizability and prevent overfitting. The model identified 8 support vectors (33.33% relative to total samples) and yielded a training and validation accuracy of 100%, which implies its potential as classification technique in chemometric analysis (as depicted in table 3). The coefficient for each support vector determines their influence on position of decision boundary. The positive coefficient indicates the support vectors define the boundary of Group A while negative suggests it belongs to group B. Further, the probability table provides the parameter used to convert SVM's decision score into probability. Rho (ρ) indicates bias which defines the offset of hyperplane from origin. The value of rho was determined to be 0.0098 during model's training. ProbA and ProbB are parameters of functions used for Platt Scaling which determines the chances of data belonging to a particular class. SVM using the formula:

$P(y=1|x) = 1/(1+e^{(Axf(x)+B)})$

[where A is prob A, B is prob B and f(x) is decision

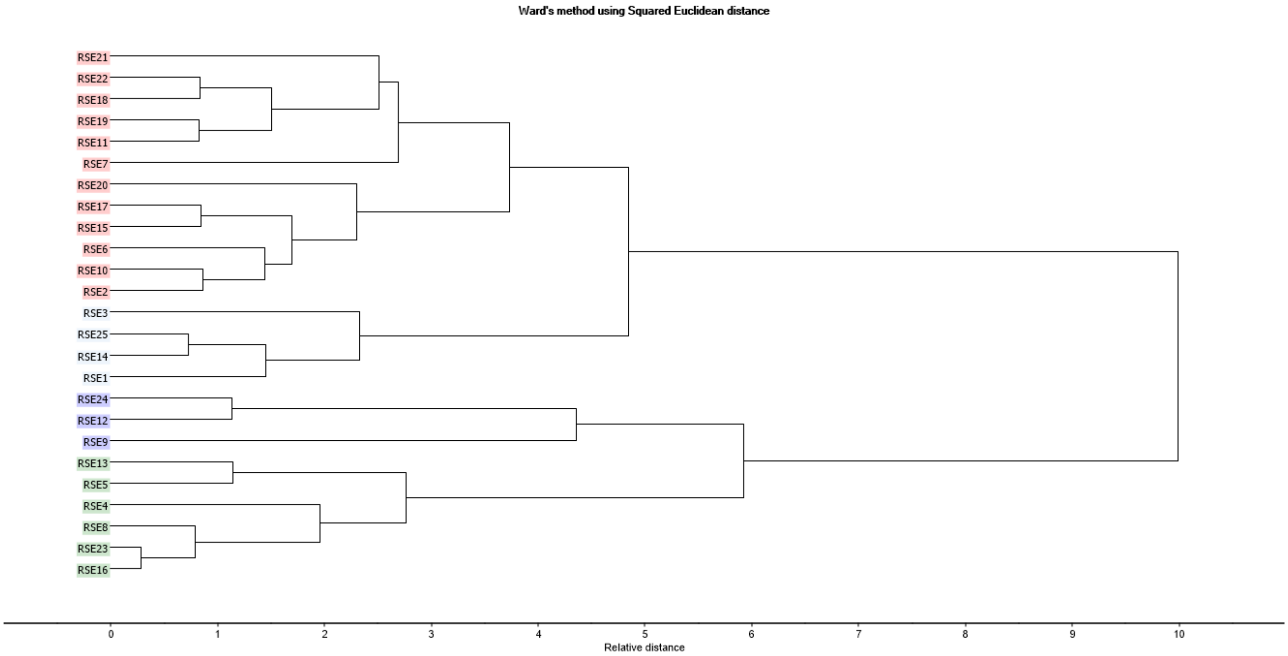

Figure 5- *Dendrogram (Wards' Method using Squared Euclidean Distance) for Clustering of Backing Spectra*

value from SVM] calculates actual probability of a sample belonging to a particular class.

3. 5. Backings

Spectral Findings

The spectral data showed the presence of Polyvinyl chloride (PVC) as the primary constituent of the backings for all the 25 samples with peaks at ~2959 cm^{-1} (asymmetric CH_3 vibration, 2926 cm^{-1} (asymmetric CH_2 vibration), 2858 cm^{-1} (symmetric CH_2 vibration), 1730-1720 cm^{-1} (C=O stretching ester group typically from phthalate), 1435-1420 cm^{-1} (CH_2 wagging), 1333 and 1254 cm^{-1} (CH bending of -CHCl group), ~960 cm^{-1} (CH_2 rocking) and distorted doublet like convoluted band in 700-600 cm^{-1} (C-Cl stretching) [28-29]. Besides PVC, spectra also showed characteristic peaks for phthalate at ~1730 cm^{-1} attributable to C=O stretching, ~1600 cm^{-1} and ~1580 cm^{-1} corresponding to C=C stretching from phthalate rings, 1130-1110 cm^{-1} and 1070-1060 cm^{-1} from C-O stretching of phthalate esters and 742 cm^{-1} due to aromatic out-of-plane bending. The band around ~873 cm^{-1} could be linked to presence of calcium carbonate as filler which is common in these tapes [5]. Further, numerous peaks in 500-400 cm^{-1} could be due to inorganic fillers used for desired properties [9].

All the samples showed relatively consistent spectra with predominant PVC backbone, phthalate or other ester-plasticizer and calcium carbonate filler. However, the spectra showed wider variation in transmittance percentage at certain peaks especially at ~1420 cm^{-1} and other peaks within fingerprint region, but it was difficult to manually identify the clusters in the samples to group them so the spectral information was subjected to cluster analysis by Wards' method using squared Euclidean distance (Figure 5).

Utilizing this method, a total of 4 groups were identified as shown in the dendrogram. The groupwise distribution of the samples are shown in the Table 4 and their representative spectra in Figure 6.

Table 4- *Groupwise Distribution of Samples according to Backing*

S. No.	Groups	Samples	Total	Distinguishing Features
1.	A	RSE2, RSE6, RSE7, RSE10, RSE11, RSE15, RSE17, RSE18, RSE19, RSE20, RSE21, RSE22	12	Prominent peaks in 1730–1720 (C=O), 1255 cm^{-1} (C-O), characteristic of phthalate plasticizer
2.	B	RSE1, RSE3, RSE14, RSE25	4	Strongest peak at ~1420 cm^{-1} as compared to other groups and 873 cm^{-1}
3.	C	RSE9, RSE12, RSE24	3	Strongest peak at 1730 cm-^{1} with relatively weaker absorption near 1420 cm-^{1}, along with pronounced peaks at 1463 cm-^{1} and 1171 cm-^{1}
4.	D	RSE4, RSE5, RSE8, RSE13, RSE16, RSE23	6	Strong peak at 1721 cm^{-1}, 1463 cm^{-1}, 1424 cm^{-1}; Peaks at 1273 cm^{-1} is exclusive to the group while the 1256 cm-^{1} band is more intense compared to the other groups.

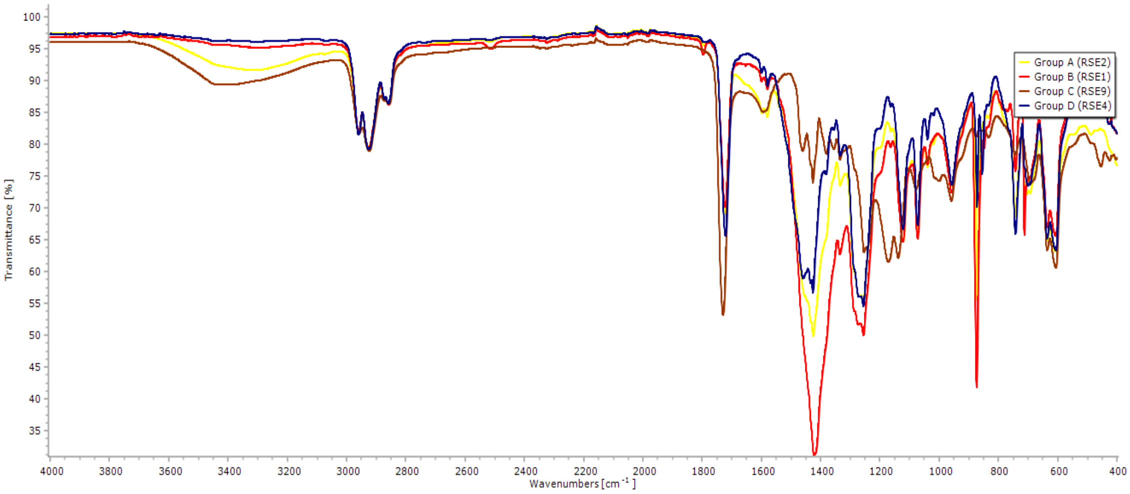

Figure 6- *Spectra of Backing Layer of Electrical Tapes (Group Representatives) [RSE2, RSE1, RSE9 & RSE4]*

3. 6. PCA

The processed spectral data was subjected to Principal Components Analysis (PCA) for dimensionality reduction. The dataset was reduced to 7 principal components using SVD algorithm, retaining 95 % variance of original data. The first PC accounted for maximum explained variance of 40% followed by PC2 (23%), PC3(12%), PC4(9%), PC5(5%), PC6 (3%) and PC7(3%). The score plot (figure 7) between PC1 and PC2 in figure explaining a total variance of 63% best depicts the distribution of four groups. The score plot shows the four groups in different colours where clusters A and B have positive PC1 values but negative PC2 values showing their relationship with these components while group D shows positive correlation with both PC1 and PC2. Samples in group C do not form a close cluster but are instead dispersed, with sample RSE9 exhibiting a negative correlation with PC1 and a strong positive correlation with PC2, whereas

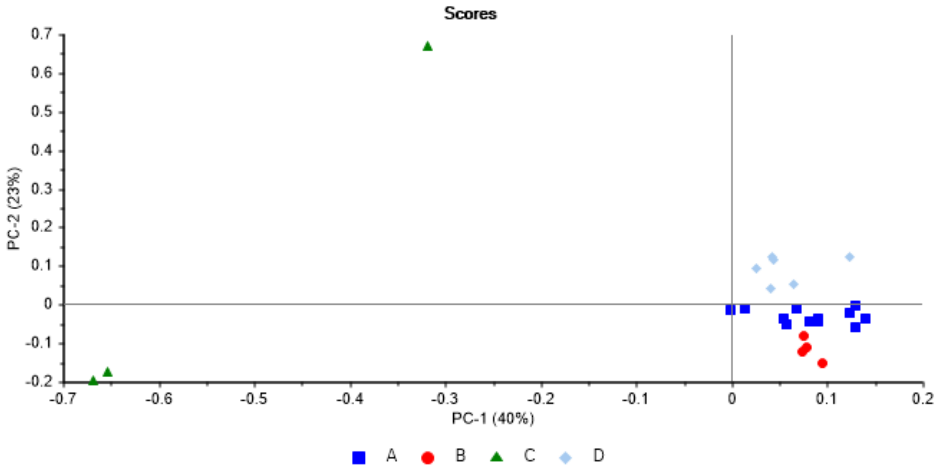

Figure 7- *Score Plot between PC1 and PC2 for Backing Layer*

Table 5- *Test of Equality of Group Means for DFA (Backings)*

	Wilks' Lambda	F	df1	df2	Sig.
PC1	.095	66.423	3	21	.000
PC2	.777	2.006	3	21	.144
PC3	.299	16.405	3	21	.000
PC4	.744	2.409	3	21	.096
PC5	.925	.571	3	21	.640
PC6	.992	.054	3	21	.983
PC7	.962	.273	3	21	.844

samples RSE12 and RSE24 display markedly negative values for both PC1 and PC2.

The 7 PCs were further used as independent variables for discriminant function analysis to assess the classification of the backing of the electrical tapes. The test of equality of group means revealed whether there are statistically significant differences among groups of independent variables. PC1 and PC3 were found to be most significantly contributing to the discriminant function ($p<.05$). The summary of the test of equality of group means is depicted in Table 5.

The present study determined discriminant functions for the classification and used first three canonical discriminant functions for analysis. Function 1 was found to be statistically most significant in discriminating with explained variance of 97.3%, eigenvalue of 296.089 and canonical correlation of .998. The three functions cumulatively accounted for 100% variance. The statistical significance of the discriminant function model and individual functions within it was further validated through wilks' lambda test. The three discriminant functions cumulatively (1 through 3) explain almost all the variance with a wilks' lambda value of .000260 and chi square value of 152.679 supporting its high statistical significance. Set of function 2 and function 3 also discriminate significantly between the groups, however with relatively higher lambda values and lower chi square values. A lambda value closer to 0 and higher chi square value suggests higher significance in discriminating (Table 6).

The combined canonical discriminant function

Table 6- *Summary of Canonical Discriminant Functions (Backings)*

	Eigenvalues			Wilks' Lambda			
Function	**1**	**2**	**3**	**Test of Function(s)**	**1 through 3**	**2 through 3**	**3**
Eigenvalue	296.089	7.753	.476	Wilks' Lambda	.0002	.077	.677
% of Variance	97.3	2.5	.2	Chi-square	152.679	47.340	7.207
% Cumulative	97.3	99.5	100.0	df	21	12	5
Canonical Correlation	.998	.941	.568	Sig.	.000	.000	.206

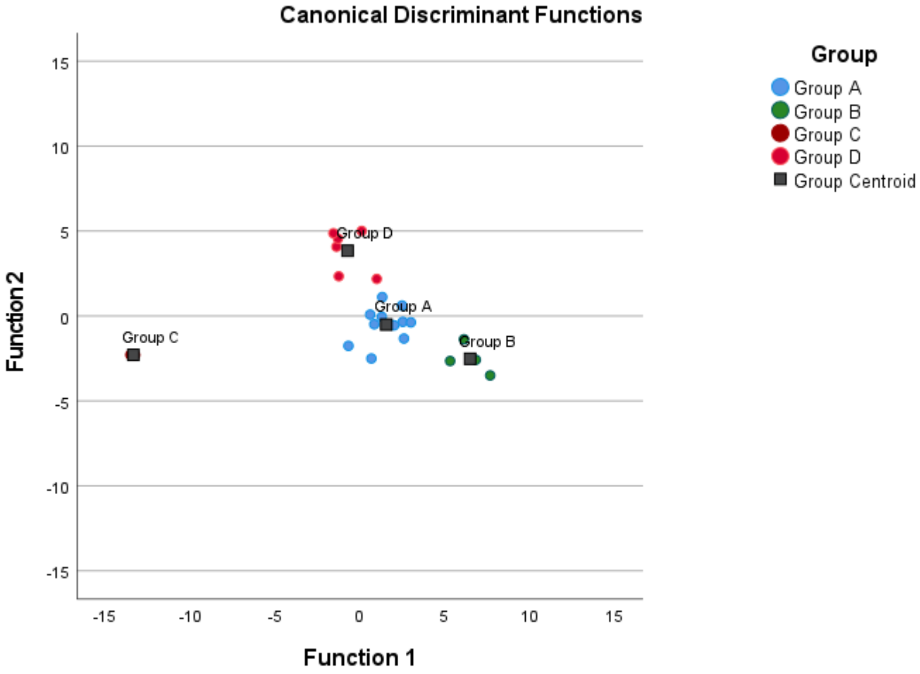

Figure 8- *Discriminant Function Plot Showing Group-wise Distribution of Samples*

plot in figure 8 shows the group wise distribution of the samples. It provides a clear separation between the four groups along with the group centroids. The model achieved an original and cross-validated accuracy of 100% and 88% respectively at classifying these backings. Sample RSE5, RSE9 and RSE13 originally belonging to group C, D and C were misclassified in cross-validation as part of group B, C and B respectively.

3. 7. Support Vector Machine (SVM)

Similar to adhesives, spectral data of backing side was also assessed using SVM for classification. SVM model was based on selected 7 PCs and was cross-validated by 10 cross-fold segments. Using C-SVC type and linear kernel with C-value of 46.41592, default gamma value of 1, determined by grid search, the model achieved a training and validation accuracy of 100% and 92% respectively. The grid search was conducted within the range, $\log_{10}$(C): –5 to 5, evaluated at ten levels The model identified a total of 18 support vectors (72% relative to total sample) as shown in table 7. Since this is a multi-class problem and SVM is inherently a binary classifier, the current model uses one-vs-rest (OvR) approach that trains a separate binary classifier for each class. In OvR, each support vector is assigned a coefficient for each n-1 classifiers, where that

Table 7- *Support Vectors and their Corresponding Coefficients (Backings)*

Identified Support Vectors	Coefficient 1	Coefficient 2	Coefficient 3
RSE1	14.15717	0.00000	0.00000
RSE3	46.41592	0.00000	0.00000
RSE14	46.41592	46.41592	3.275954
RSE25	0.00000	0.00000	1.228116
RSE6	0.00000	38.79177	0.00000
RSE7	0.00000	1.242604	0.00000
RSE10	-24.8773	0.00000	0.00000
RSE11	-29.6336	46.41592	3.75136
RSE15	0.00000	6.381546	0.00000
RSE19	-46.4159	0.00000	0.00000
RSE20	-3.97986	0.00000	2.047249
RSE22	-2.08239	0.00000	0.00000
RSE5	0.00000	-46.4159	0.00000
RSE8	0.00000	0.00000	2.37664
RSE13	-46.4159	-46.4159	3.222693
RSE9	-1.88461	-2.5024	-2.59841
RSE12	0.00000	-3.29622	-3.00093
RSE24	-2.61946	0.00000	0.00000

Table 8- *Confusion Matrix for SVM Model of Backing Layer*

Actual → Predicted ↓	Group A	Group B	Group C	Group D
Group A	12	0	0	0
Group B	0	4	0	0
Group C	0	0	3	0
Group D	0	0	0	6

support vector is part of "other" group, thus resulting three coefficients in present study. These coefficients reveal the influence of that specific support vector on a specific binary classifier. RSE14 and RSE9 has three positive and negative non-zero coefficients respectively, indicating its influence on decision boundaries of three different classifiers. The largest coefficients observed are around 46.41592 (e.g., RSE3, RSE14, RSE11, RSE19, RSE13, RSE5), suggesting these points are the most influential support vectors for the boundaries they affect. The coefficient magnitude of 0 suggest that, these have minimal impact on classification for that particular class's decision boundary. Some vectors further displayed non-zero coefficients across multiple functions indicating their relevance in separating more than one class boundary within multi-class framework. The confusion matrix in table 8 shows that each group achieved an accuracy of 100% in classification. While the SVM model performed comparatively better than the discriminant model but its efficiency needs to be further corroborated by larger amount of training and testing data.

4. DISCUSSION

Electrical Tapes are one of the most common PSA tapes along with duct tapes often submitted to Crime laboratories because of its widespread use for a multitude of purposes by criminals and deviants to perpetrate crimes. However, its most commonly reported application by criminals is in assembling electrical components of improvised explosive devices (IEDs) but its use is not limited to that. These can be found as evidence or exhibits associated with crimes such as burglary, theft and smuggling of contrabands.

A number of studies attempted to determine the chemical constituents of the adhesives and the backing sides of the electrical tapes and to classify them. However, the composition of these tapes is affected by time, location of origin, price of raw materials, purpose of use and manufacturers' brand value and several other factors. The present study analysed electrical tape samples from 25 different manufacturers using ATR-FTIR integrated with chemometrics. The analysis was carried for both the adhesives and backing sides of the tapes to determine its chemical constituents and classify them. The study identified rubber and acrylics as the predominant elastomers used for adhesives while PVC with phthalate and calcium carbonate as the primary components of the backing. Keto (1984) reported SBR as the main constituent of adhesives of these tapes while Mehltretter et al. (2011) classified adhesives of electrical tapes into 8 groups, majority of which were either rubber-based or acrylic based. This is in concordance with the present study [1] [14]. Mehltretter et al. (2011) in another study on the backing of electrical tapes identified PVC as the backbone of the electrical tapes. However, the study by Mehltretter also reported use of polyethylene and butyl rubber as backing in some tapes which was not the case in the present study [5]. Zięba-Palus (2016) also studied the adhesive and backing sides of different tapes which included electrical tapes beside duct tapes and packaging tapes using ATR-FTIR. The study classified backing sides into polypropylene, polyethylene, polyester and acetylated cellulose and didn't report PVC as backing in any of the tapes. Adhesive sides were also classified as rubber with styrene, polyester, butadiene-styrene and acrylics however, the study didn't specifically mention the type of adhesives in electrical tapes [17].

The literature on chemometric analysis of IR spectra of electrical tapes is quite scarce. One such study by Nimi et al. (2022) employed chemometric classification viz. PC-LDA to classify adhesive and backing side of electrical tapes based on ATR-FTIR. Nimi et al. reported classification accuracies of 92.98% for adhesives and 88% for backing sides, with corresponding validation accuracies of 89.47% and 84% [18]. In the present study, PC-DFA model yielded original and cross-validated accuracies of 100% for adhesive sides, and 100% and 88% for backing sides, respectively. The study further assessed SVM models for the classification of samples based on the same groups as used in discriminant analysis. The SVM approach outperformed discriminant models for backing side, achieving higher accuracy on held-out sets and offering more robust decision boundaries, even with small-to-moderate sample sizes. While prior reports on the application of SVM for chemometric classification of tapes are scarce, the present findings preliminarily suggest it as a promising alternative capable of handling limited data effectively.

The courtroom acceptability of such scientific evidences and techniques rely on degree to which it fulfils the conditions set forth by Daubert standard which emphasizes empirical testability, peer review and known potential error rates. The error profile observed in the current study with near perfect classification of 25-sample set (CI: 95%) is encouraging, however, interpretation is limited by smaller sample size and non-accountability of aging, environmental factors etc., underscoring the need for robust external validation for admissibility in court. The results of the models should be considered as research level-findings rather than court-admissible proof at this stage and admissibility in judicial proceedings would further require methodology harmonization and demonstration of inter-laboratory reproducibility. The study further reports internal cross-validation results for the models which needs to be further corroborated against inter-laboratory error rates and false classification probabilities using broader validation strategies according to ASTM E3260-21 and in accordance with the Organization of Scientific Area Committee (OSAC) standard guide for Forensic Examination of PSA tapes.

5. CONCLUSIONS

ATR-FTIR is a vital analytical technique often used for characterization, classification and discrimination of materials often potentially recovered as evidences at the crime scene. The current study underscores its potential as a non-invasive and non-destructive technique for preliminary identification of the chemical composition of adhesives and backing sides of electrical tapes and classify them. The study revealed majority of electrical tapes available in Indian markets predominantly use rubber or acrylic based adhesives and PVC backings. The backings were also found to contain phthalates as plasticizers and calcium carbonate as fillers in the backing. Further chemometric based classification was employed on spectral data to classify adhesive and backing side. The PC-based discriminant analysis model achieved classification accuracies of 100% for both the adhesive sides and the backing sides, while yielding cross-validated accuracies of 100% and 88%, for sides respectively. The study demonstrates IR spectral data integrated with chemometrics can be of great aid in classifying and discriminating tapes. The study also attained perfect (100%) training and validation accuracy for adhesive classification, and 100% training accuracy with 92% validation accuracy for backing preliminarily when employing the SVM classification model. However, the present study requires further corroboration and validation through investigations on actual crime scene samples, with larger sample sizes, using advanced machine learning software and under varied environmental conditions to fully evaluate its true potential.

LIMITATIONS

While the study demonstrates FTIR with chemometrics as a potential tool for classification of electrical tapes on the basis of chemical constituents and can serve as exclusionary apparatus in analysing crime scene exhibits. The potential limitations of the study include

- Limited sample size, with many manufacturers using identical formulations which makes it difficult to classify the samples manufacturer-wise solely on the basis of spectral information. The limitation can be curbed by using other analytical techniques in combination with FTIR.
- The study doesn't analyse the effects of aging and environmental exposure, however, future models must take these factors into account for enhanced model transferability in actual crime investigation.
- All the spectra were collected from same instrument and by same operator, thus inter-instrument and inter-operability reproducibility were not tested, resulting in limited external generalisability.

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Conflict of interest

The authors declare no conflicts of interest.

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