MACHINE LEARNING-ASSISTED CLASSIFICATION OF GUNSHOT RESIDUE (GSR) PARTICLES BASED ON SCANNING ELECTRON MICROSCOPY-ENERGY DISPERSIVE X-RAY SPECTROSCOPY (SEM-EDX) SPECTRAL DATA

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ABSTRACT

Machine Learning (ML) algorithms have become essential for forensic science, helping with the more accurate and objective analysis of evidence. The current study discusses the use of ML algorithms in classifying gunshot residue (GSR) particles by analysing spectral data acquired with scanning electron microscopy in combination with energy-dispersive X-ray spectroscopy (SEM-EDX). Traditionally, GSR analysis is based on finding inorganic particles that contain Lead (Pb), Barium (Ba), and Antimony (Sb), indicating discharge from firearm primer in Forensic science. Twelve Spectra were generated as samples from four hand swabs taken from a simulation where a suspect just shot some bullets using a firearm. Control samples produced no result. GSR were examined to evaluate elemental distribution and ML-assisted classification. In addition, a statistical analysis of SEM-EDX spectra was performed along with probabilistic modelling, and likelihood ratios (LRs) were used to measure the evidential weight between two hypotheses. ML algorithms assisted in separating typical GSR particles from those belonging to other types. The research showed considerable differences in elemental composition between the samples, demonstrating the necessity of applying appropriate statistical tools. Three out of the four classes of swab samples provided a solid ground for proving GSR presence and produced high LRs in favour of the prosecution hypothesis. At the same time, only one sample failed to comply with the model assumptions, demonstrating the risk of misinterpretation when using elemental signatures alone. All in all, the application of ML in combination with probabilistic modelling can provide a solid basis for forensic science analysis of gunshots, but there should be no room for neglecting methodology issues.

KEYWORDS

GSR, Pb-Ba-Sb, SEM-EDX, likelihood ratios, Machine Learning.

1. INTRODUCTION

Gunshot residue (GSR) is generated during firearm discharge and consists of a complex mixture of primer combustion products, partially burned propellant, and metallic particles. These residues are typically deposited on the hands, clothing, and surrounding surfaces of individuals in proximity to the discharge event [1, 2].

Unlike more persistent forensic evidence such asdeoxyribonucleic acid (DNA), Gun-shot residue(GSR) is highly transient and susceptible to environmental loss, secondary transfer, and contamination [3]. Consequently, its presence can indicate proximity to a firearm discharge but cannot conclusively establish that an individual fired a weapon.
Modern forensic analysis relies on SEM-EDX for the identification of characteristic inorganic GSR particles, particularly those containing Pb, Ba, and Sb [4]. However, interpretation increasingly incorporates statistical modelling and likelihood-based frameworks to evaluate evidential strength [5].

The aim of this study was to quantitatively characterize GSR particles from simulated hand swabs. The objectives of the study were to apply probabilistic modelling to elemental data and evaluate evidential strength using likelihood ratios.

2. RELATED WORK

Recent progress in GSR analysis includes the focus on improved detection, recovery, and interpretation on different substrates. Researchers found that there could be other sampling sources, like the surgical mask and deteriorated biological samples [6, 7]. It is important to note that the SEM-EDX and ICP-MS techniques are crucial when considering the inorganic GSR analysis, and at the same time, the combination of organic and inorganic analysis leads to more valuable evidence [8, 9]. Moreover, the new methods developed for GSR analysis, like fluorescence, increase the sensitivity of the analysis [10]. This progress makes machine learning necessary for gun crime investigation.

3. METHODOLOGY AND APPROACH

3.1. Sample Collection and Procedures

There were four swab samples collected from a simulated suspect's hands, targeting areas known for high GSR deposition, like the webbing between thumb and forefinger, both palmar and dorsal surfaces. Chain-of-custody procedures were followed as required in all forensic investigations. Control samples were also collected, which showed no detectable Lead (Pb), Barium (Ba), or Antimony (Sb).

3.2. Sample Preparation and Analysis

All four Samples were mounted on SEM stubs and analyzed using SEM-EDX. Elemental compositions were obtained across multiple spectra per sample.

4. RESULTS

The following results were obtained from SEM-EDX as shown in Table 1.

Table 1: Twelve (12) Spectral of GSR samples

Total Swabs	**12 Spectral**	**Pb**	**Ba**	**Sb**
Swab 1	Spectrum 1	0.90	37.29	0.65
	Spectrum 2	17.51	ND	25.69
	Spectrum 3	19.54	ND	25.32
	Average	**12.65**	**37.29**	**17.22**
	Standard Deviation	**10.23**	**21.53**	**14.35**
Swab 2	Spectrum 4	27.46	ND	22.65
	Spectrum 5	ND	44.73	1.21
	Spectrum 6	ND	25.69	0.59
	Average	**27.46**	**23.47**	**8.15**
	Standard Deviation	**15.85**	**22.44**	**12.56**
Swab 3	Spectrum 7	24.46	29.82	11.60
	Spectrum 8	18.71	26.36	19.90
	Spectrum 9	20.11	29.06	11.91
	Average	**21.09**	**28.41**	**14.47**
	Standard Deviation	**3.00**	**1.82**	**4.70**
Swab 4	Spectrum 10	5.45	28.60	30.33
	Spectrum 11	ND	ND	ND
	Spectrum 12	7.55	34.57	37.52
	Average	**4.33**	**21.06**	**22.62**
	Standard Deviation	**3.95**	**18.11**	**20.06**

Note: ND means not detected. From the first SEM–EDX swab, Barium (Ba) appears only in Spectrum 1 with a value of 37.29 wt%. Spectra 2 and 3 list no Ba value (blank), which means *no detected Ba* rather than a numerical zero. Therefore, the statistical results for Ba are based on a single measured value:

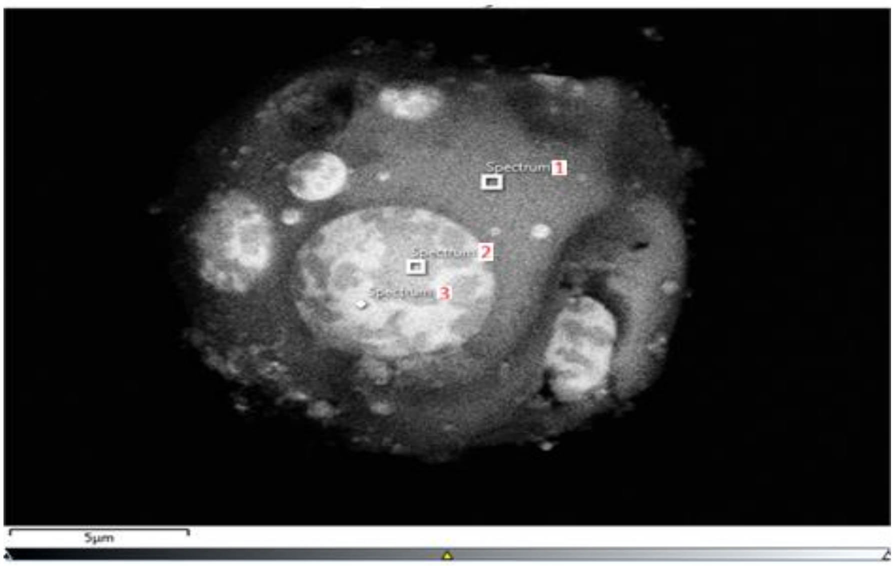

Figure 1: Electron Image 1(Spectra 1 to 3)

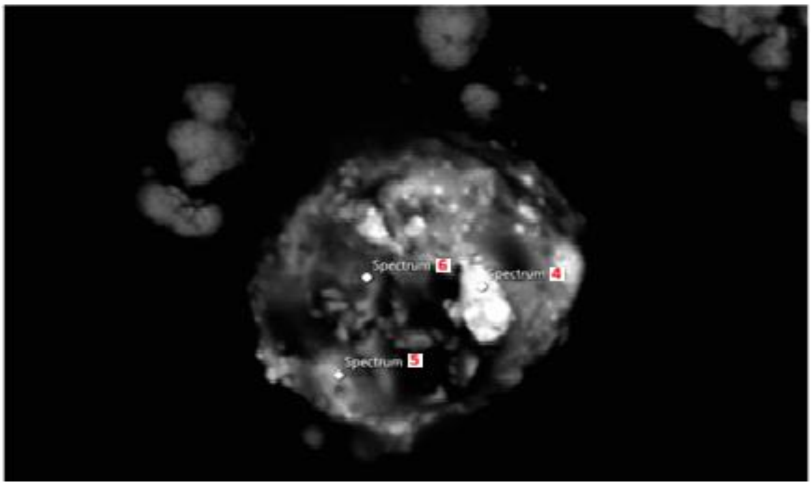

Figure 2: Electron Image 2(Spectra 4 to 6)

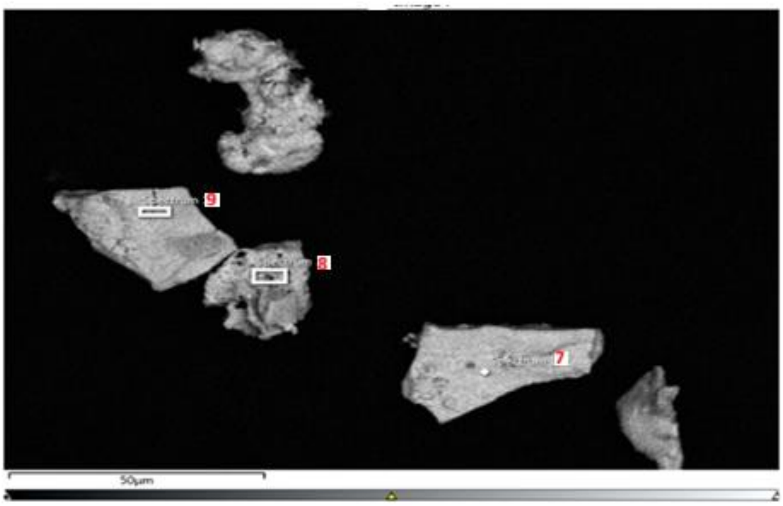

Figure 3: Electron Image 3 (for Spectra 7 to 9)

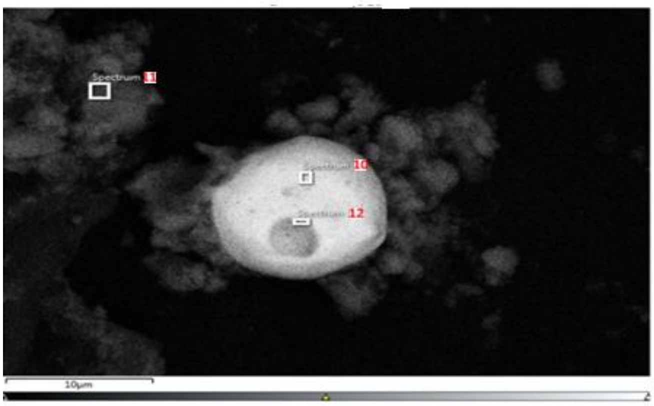

Figure 4: Electron Image 4 (for Spectra 10 to 12)

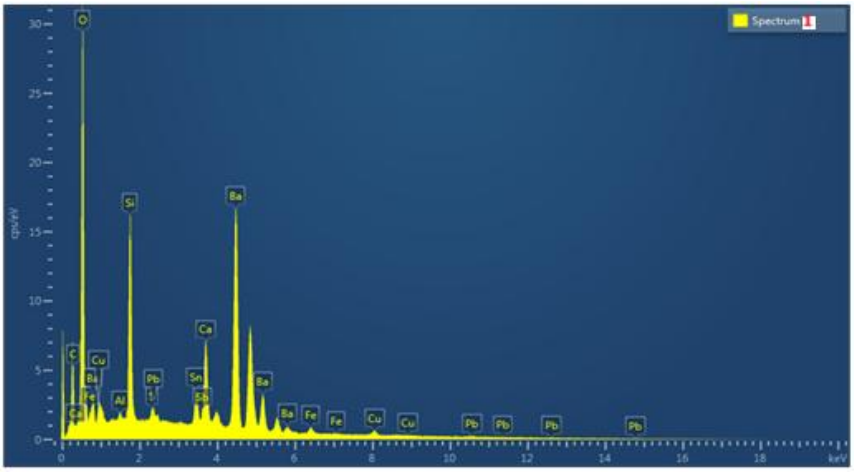

Figure 5: Spectrum 1

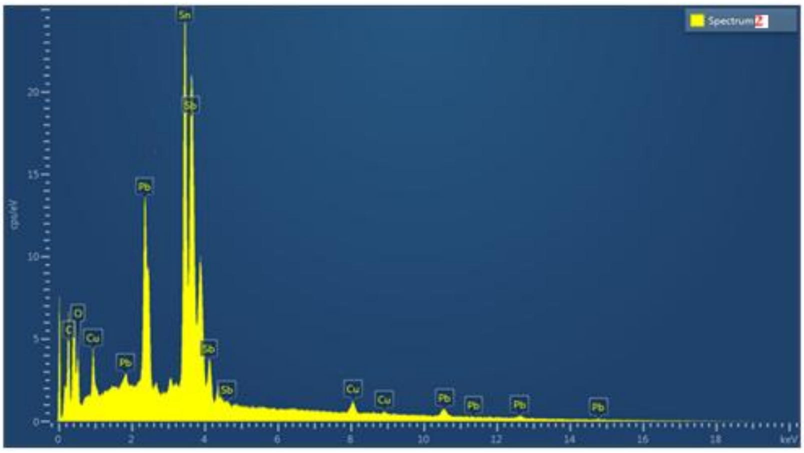

Figure 6: Spectrum 2

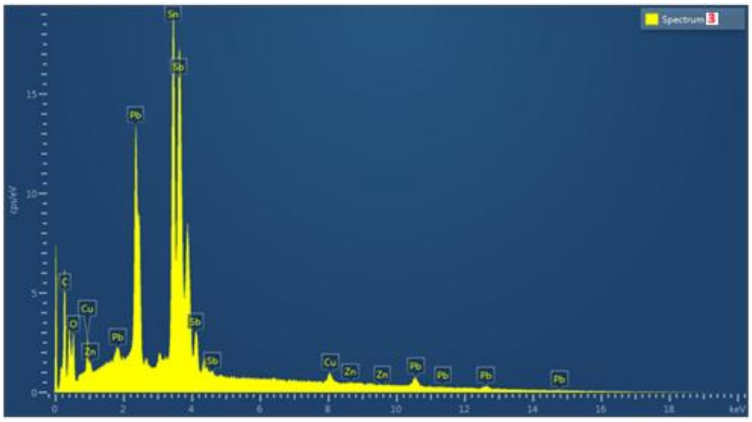

Figure 7: Spectrum 3

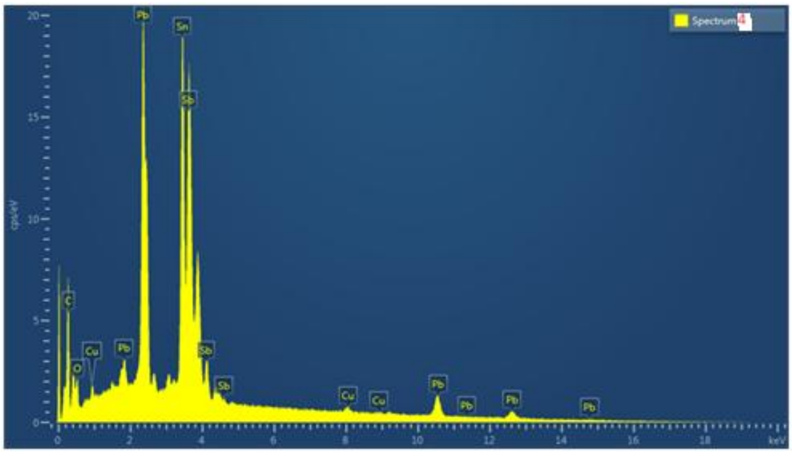

Figure 8: Spectrum 4

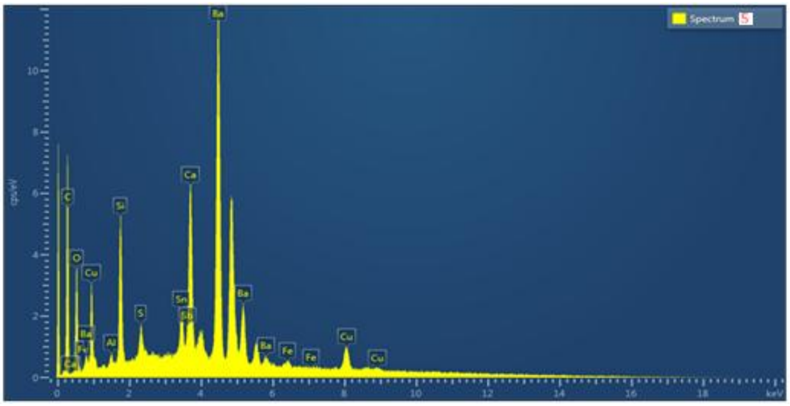

Figure 9: Spectrum 5

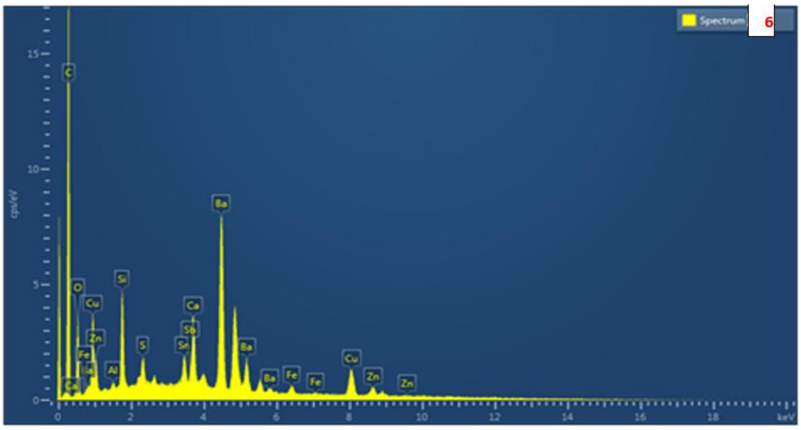

Figure 10: Spectrum 6

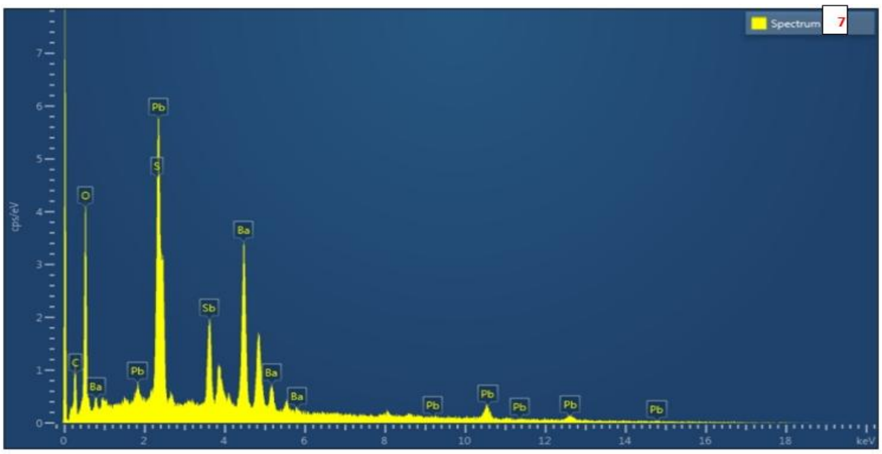

Figure 11: Spectrum 7

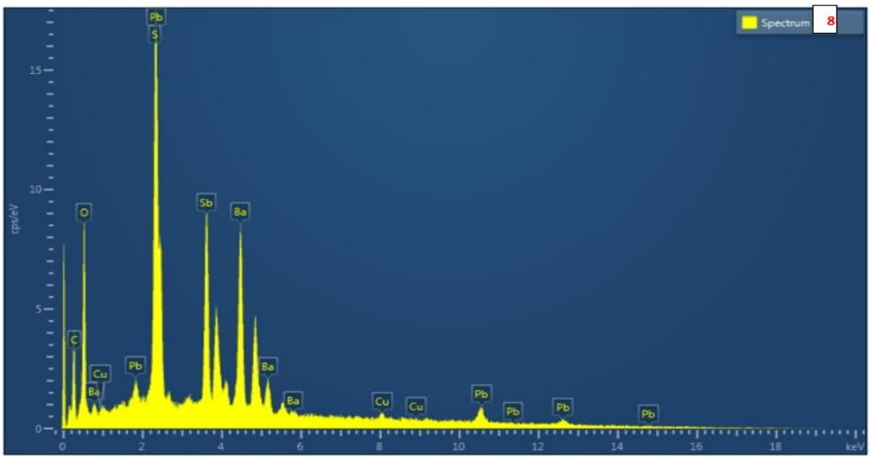

Figure 12: Spectrum 8

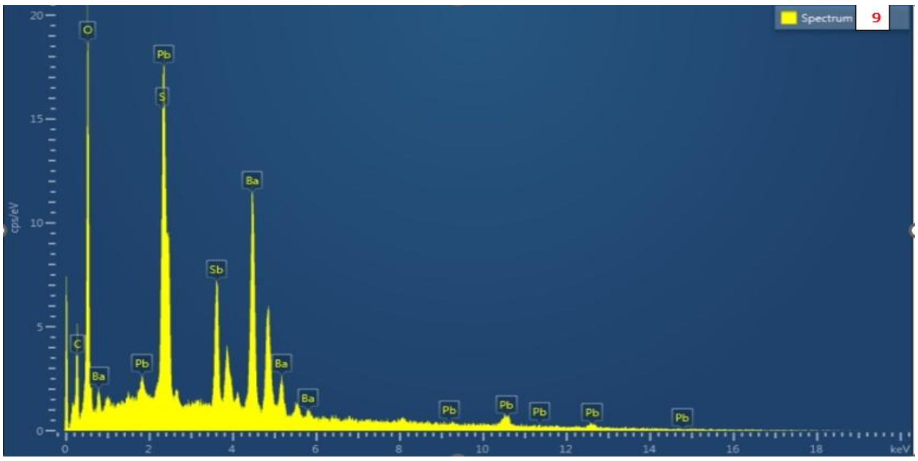

Figure 13: Spectrum 9

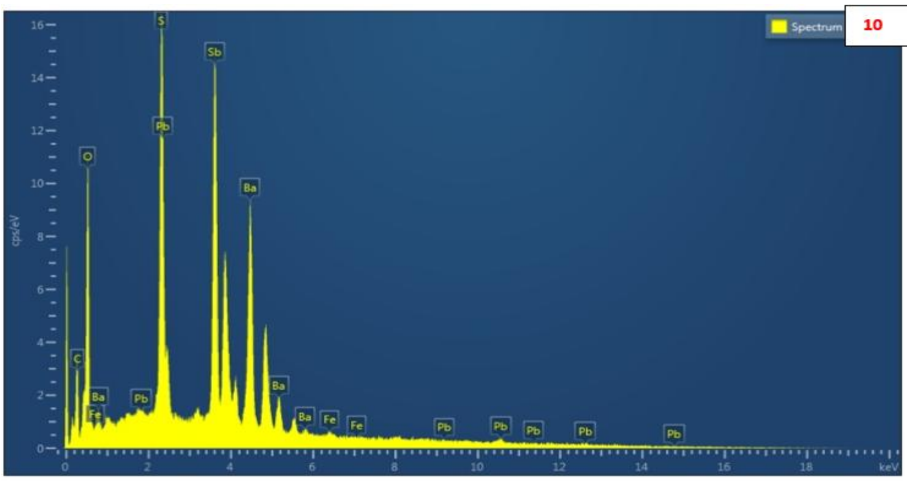

Figure 14: Spectrum 10

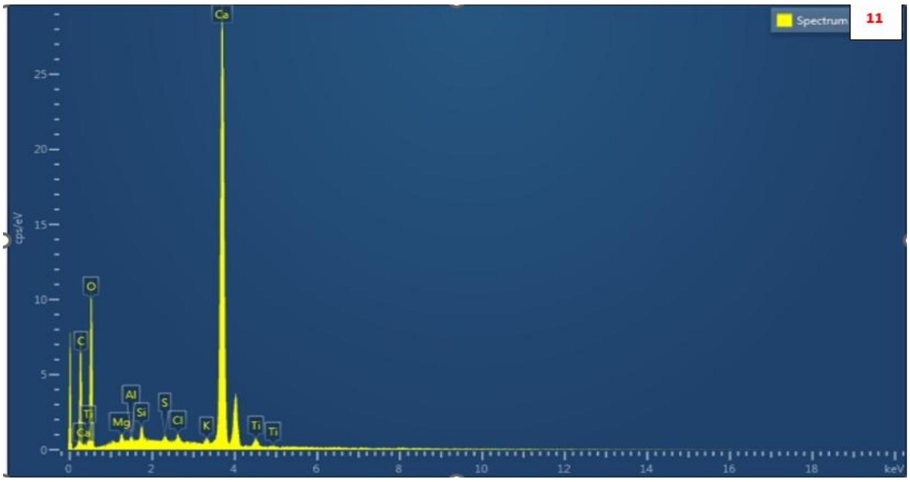

Figure 15: Spectrum 11

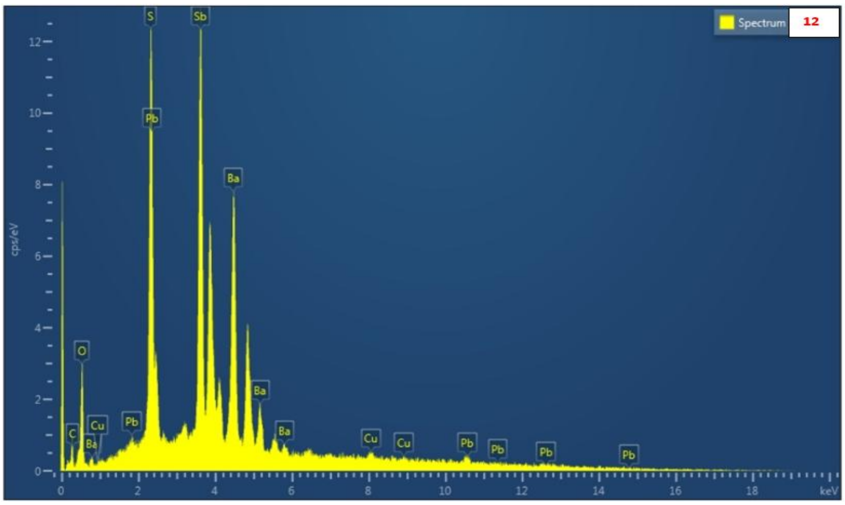

Figure 16: Spectrum 12

4.1. Statistical Treatment

For each element (Pb, Ba, Sb), mean and standard deviation were calculated. Where only a single measurement existed, standard deviation was treated as zero or undefined.
Suggested characteristic GSR compositional ranges were adopted:

1. Pb: 1 to 20 wt%
2. Ba: 30 to 70 wt%
3. Sb: 5 to 35 wt%

Table 2: Forensic Science Service Classification of the Elemental Composition

FSS (Forensic Science Service Classification)	FSS Types
Pb, Ba, Sb	1
Pb, Ba, Sb, Al	2
Pb, Ba, Sb, Sn	3
Pb, Ba, Ca, Si	4
Pb, Ba, Sb, Ca, Si, Sn, Al	5

These ranges reflect accepted forensic guidelines rather than fixed standards [2, 4].

4.2. Elemental Composition

Table 3: Results of Elemental Composition

Composition	Swab 1	Swab 2	Swab 3	Swab 4
Pb	12.65 ± 10.23	27.46 (single value)	21.09 ± 3.00	6.50 ± 1.48
Ba	37.29 ± 0.00	35.21 ± 13.46	28.41 ± 1.82	31.59 ± 4.22
Sb	17.22 ± 14.35	8.15 ± 12.56	14.47 ± 4.70	3 5.08

Note: Standard Deviation:

$$s = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2}{2 - 1}}$$

Standard Deviation: This is not possible to be defined for a single data point; therefore, the result suggests entering 0 or leaving blank (Other entries with one value appear to leave SD blank).

4.3. Probability Modelling

Each elemental concentration was modelled as normally distributed using observed mean and standard deviation. The probability of each element falling within GSR characteristic ranges was computed using the cumulative normal distribution.
Assumptions:
1. Independence between elements
2. Normal distribution of measurements
3. Zero standard deviation treated as point values

4.4. Joint Probabilities

Joint probabilities (all elements within range):
1. Swab 1: 0.442

2. Swab 2: 0.000
3. Swab 3: 0.067
4. Swab 4: 0.377

4.5. Likelihood Ratio Evaluation

4.5.1. Hypotheses

1. Hp: Particles originate from GSR
2. Hd: Particles originate from environmental/background sources

4.5.2. Background Models

Two illustrative background scenarios were used:
1. Typical background
2. Conservative background

These represent assumed probabilities of environmental particles falling within GSR ranges [3,11].

4.5.3. Likelihood Ratios

Table 4: Likelihood Ratios

Sample	LR (Typical)	LR (Conservative)
Swab 1	8,847	442
Swab 2	0	0
Swab 3	1,339	67
Swab 4	7,547	377

4.6. Discussion of Result

The results demonstrate variability in elemental composition across samples, consistent with previous findings that GSR particles do not exhibit fixed compositional ratios [12, 13].

Samples from Swab 1, Swab 3, and Swab 4 provided staunch support for the GSR hypothesis, particularly under the typical background model. However, Swab 2 yielded an LR of zero due to Pb concentration exceeding the defined range, illustrating the sensitivity of probabilistic models to strict parameter assumptions.

This highlights several important considerations:

1. GSR interpretation is highly dependent on model assumptions.
2. Elemental independence may not fully reflect real-world particle formation.
3. Measurement uncertainty should be incorporated to avoid absolute conclusions.

The findings align with current forensic trends emphasising probabilistic reporting over categorical conclusions [5].

4.6.1. Limitations

The general limitations as recorded in previous studies, such as environmental contamination: Background particles mimicking GSR [3] and Transfer and persistence: Secondary transfer and rapid loss of GSR [14]

5. CONCLUSIONS

This study demonstrates the value of combining SEM–EDX analysis with probabilistic modelling in GSR interpretation. While elemental composition provides strong evidential support in several cases, results are highly sensitive to statistical assumptions and background models.

Likelihood ratios offer a robust framework for evaluating evidential strength but must be applied cautiously, with transparent assumptions and acknowledgment of limitations. GSR evidence should always be interpreted within the broader forensic context, including transfer mechanisms and case circumstances.The combination of SEM–EDX analysis with probabilistic modelling used in this study, was able to alleviate the majority of the limitations encountered by previous studies.

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