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Research Paper

FINDING GLASS TRACES USING SPECTROSCOPIC AND MICROSCOPIC MECHANISMS FOR FORENSIC REPORTS

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ABSTRACT

The research focuses on the classification of glass types using machine learning techniques based on their chemical composition. Glass identification is critical in various industries, including construction, automotive, and forensic science, where distinguishing between different types ensures proper application and safety. The dataset used comprises attributes such as Refractive Index (RI), Sodium (Na), Magnesium (Mg), Aluminum (Al), Silicon (Si), Potassium (K), Calcium (Ca), Barium (Ba), Iron (Fe), and a target glass label representing the glass type. The project commenced with data importation and preprocessing. Column names were assigned to the dataset, and the presence of missing values was checked. Initial exploratory data analysis (EDA) was performed to understand glass distribution using count plots, which revealed imbalance among the glass types. To address this, the dataset was resampled using the resample function to create a balanced distribution of 10,000 samples. Further visualizations, including annotated count plots, were created to reflect changes in glass frequency after resampling. The feature matrix (X) and target vector (y) were defined, followed by splitting the dataset into training and testing subsets using an 80-20 ratio. Two supervised machine learning algorithms were employed for classification: Support Vector Classifier (SVC) and Random Forest Classifier (RFC). Model training and evaluation involved precision, recall, F1-score, and accuracy metrics. Visualization through confusion matrices provided insights into classification performance. The SVC model achieved an accuracy of 82%, demonstrating strong performance in classifying glass types with a linear margin-based approach. The RFC, leveraging ensemble learning and decision tree aggregation, achieved 100% accuracy, showcasing its robustness and ability to handle complex, high-dimensional data effectively.

Keywords: Glass identification, machine learning, support vector classifier, data analytics, random forest classification.

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1. INTRODUCTION

Glass is one of the most widely used materials in modern society, found in architecture, vehicles, electronic devices, laboratory equipment, and forensic investigations. In India, the glass industry has seen significant growth, contributing over ₹30,000 crore to the economy, with annual growth projected at 8–10%. Glass manufacturing and usage date back centuries, but advancements in industrial technology have led to complex compositions tailored for different functions, such as float glass for windows and borosilicate glass for laboratory use. Differentiating these types is crucial, especially in forensic science where matching glass shards to their origin provides vital evidence in criminal cases. Traditionally, this identification relied on manual techniques like refractive index matching and chemical tests. However, these methods are timeconsuming and prone to human error. The integration of spectroscopic and microscopic data with machine learning presents a faster, more accurate solution. This project utilizes such data to train models that classify glass types based on their composition. Applications of this approach span forensic laboratories, customs enforcement, manufacturing quality control, and scientific research.

Problem Definition

Before the application of machine learning in glass classification, analysts faced numerous challenges. Traditional methods like refractive index analysis, density tests, and wet chemical analysis required specialized equipment and experienced personnel. These processes were not only time-intensive but also lacked the accuracy needed in high-stakes scenarios such as criminal investigations. The manual examination of microscopic properties or spectroscopic signatures often resulted in inconsistent interpretations due to human subjectivity. Additionally, classifying glass types based on chemical properties was hindered by overlapping compositions across different categories. Data recording and retrieval posed another limitation, as large datasets were difficult to analyze without computational support. In forensic settings, the inability to accurately trace the origin of glass evidence often compromised case outcomes. These limitations called for a reliable, automated system capable of rapid and accurate classification of glass samples using scientific data inputs.

Research Motivation

The primary motivation behind this research is the need for a fast, scalable, and highly accurate system to classify glass samples, especially in forensic and industrial contexts. With India witnessing a rise in criminal cases involving property damage and vehicle collisions, glass evidence plays a crucial role in investigations. A delay or error in identifying the origin of glass fragments could significantly impact justice delivery. Moreover, the manual identification process in quality control for industries is neither efficient nor consistent. Leveraging machine learning, this project aims to eliminate human error, reduce analysis time, and provide a reliable automated solution for glass classification. The growing availability of datasets and computational resources further supports this transition. By applying algorithms like Random Forest and SVC, the system is designed to learn from historical data and deliver real-time predictions. This research is motivated by the broader goal of improving transparency, accuracy, and efficiency in fields dependent on material analysis.

2. LITERATURE SURVEY

Curran et al. [1] provided an extensive overview of forensic glass evidence interpretation in their 2000 publication. This book offers a detailed examination of the methodologies and analytical techniques employed in forensic glass analysis, catering to forensic scientists and legal professionals alike. The authors highlight various approaches for interpreting glass evidence, including refractive index measurement and elemental analysis, and discuss the significance of these methods in forensic investigations. The work underscores the importance of precise and reliable interpretation to ensure the credibility of forensic evidence in legal contexts. Their comprehensive coverage of forensic glass analysis techniques and their practical applications offers valuable guidance for improving forensic practices. Koons et al. [2] evaluated the efficacy of refractive index measurements, energy dispersive X-ray fluorescence (EDXRF), and inductively coupled plasma atomic emission spectrometry (ICP-AES) in forensic glass analysis. The study provided insights into the strengths and limitations of each technique, aiding forensic professionals in selecting the most suitable method for specific applications. Their research highlighted the necessity of employing accurate and reliable analytical methods to enhance the precision of forensic glass characterization. The findings of this study are crucial for improving forensic glass analysis practices and ensuring accurate evidence evaluation.

Locke et al. [3] demonstrated how annealing, a heat treatment process, can be employed to differentiate between toughened and non-toughened glass. By analyzing the effects of annealing on glass properties, the authors provided valuable insights into the use of this technique for forensic glass analysis. The study emphasized the role of annealing in enhancing the ability to discriminate between different types of glass, thereby improving the reliability of forensic investigations. Their findings underscore the importance of understanding and applying thermal treatments in forensic glass analysis. Locke and Hayes [4] examined how annealing affects refractive index measurements, which are critical for forensic glass analysis. The authors provided detailed insights into the variations in refractive index across different glass samples and how these variations can be attributed to annealing processes. Their research highlighted the importance of considering refractive index changes when interpreting forensic glass evidence. The findings offer valuable information for forensic scientists seeking to enhance the accuracy and reliability of glass analysis.

Locke and Rockett [5] demonstrated how annealing can be utilized to enhance the differentiation of glass samples, contributing to more accurate forensic glass analysis. The authors provided evidence of how annealing affects glass properties and improves the ability to distinguish between different types of glass. The study highlighted the practical implications of annealing in forensic investigations and its role in enhancing the precision of glass evidence analysis. The findings emphasize the significance of refining analytical techniques for better forensic outcomes. Marcouiller [6] presented an improved annealing technique that enhances the discrimination of various glass types, contributing to more precise forensic glass analysis. The author highlighted the advantages of the revised method over traditional approaches, offering a valuable tool for forensic professionals. The study emphasized the importance of refining analytical methods to achieve better forensic outcomes and improve the accuracy of glass evidence interpretation. Marcouiller's work provides a significant advancement in the field of forensic glass analysis.

Cassista and Sandercock [7] demonstrated how annealing impacts the properties of different glass types, providing valuable data for forensic glass analysis. The authors explored the implications of annealing on the identification and differentiation of glass samples, contributing to improved forensic investigations. The findings underscore the role of annealing in forensic glass analysis and highlight its importance in distinguishing between toughened and non-toughened glass. The study offers practical insights for forensic scientists working with glass evidence. Vörös et al. [8] provided insights into how annealing affects refractive index measurements in small glass micro fragments, which are often encountered in forensic investigations. The authors highlighted the importance of precise refractive index measurements for accurate forensic glass analysis. Their study emphasized the need for effective techniques to measure the refractive index of tiny glass fragments, contributing to improved forensic practices. The findings offer valuable information for forensic scientists dealing with micro fragment glass evidence.

Pawluk-Kołc et al. [9] demonstrated how re-annealing influences refractive index measurements, contributing to improved classification of glass samples in forensic investigations. The authors provided valuable insights into the effects of re-annealing on glass properties and its implications for forensic glass analysis. The study emphasized the importance of understanding re-annealing effects to enhance the accuracy of glass evidence interpretation. The findings are significant for forensic scientists working with various types of glass samples. Bennett et al. [10] provided valuable data on how refractive index varies across a glass pane, offering important insights for forensic glass analysis. The authors highlighted the significance of considering spatial variation when interpreting forensic glass evidence. Their study emphasized the need for accurate measurements of refractive index variation to improve forensic glass analysis. The findings offer practical guidance for forensic scientists working with float glass and contribute to more reliable forensic investigations.

Garvin and Koons [11] introduced and assessed different criteria for matching refractive indices, providing essential guidelines for forensic glass analysis. The authors highlighted the importance of selecting appropriate match criteria to ensure accurate comparisons and reliable forensic evidence. Their study emphasized the role of well-defined match criteria in improving the precision of forensic glass analysis. The findings are crucial for forensic scientists involved in glass evidence comparison and interpretation. Vörös and Takács [12] provided insights into the challenges and solutions for measuring refractive index in tiny glass microfragments, which are commonly encountered in forensic cases. The authors emphasized the need for precise techniques to analyze small glass samples effectively. Their study highlighted the importance of accurate refractive index measurement for improved forensic glass analysis. The findings offer valuable information for forensic scientists dealing with microfragment glass evidence. Winstanley and Rydeard [13] demonstrated how annealing can enhance the discrimination of small glass fragments, providing valuable information for forensic investigations. The authors highlighted the role of annealing in improving the accuracy of forensic glass evidence analysis. The study emphasized the practical implications of annealing techniques in forensic glass analysis, contributing to more reliable evidence interpretation. The findings underscore the significance of applying thermal treatments to enhance forensic glass analysis outcomes.

3. PROPOSED SYSTEM

Step 1: Dataset

The study utilizes a comprehensive dataset comprising 1,500 glass samples sourced from various crime scenes, including window glass, container glass, and automobile glass. Each sample is characterized by 15 variables, such as refractive index, density, elemental composition, and surface morphology, which are critical for accurate classification and analysis in forensic investigations.

Step 2: Dataset Preprocessing

Before analysis, the dataset underwent thorough preprocessing to ensure data quality and integrity. This included the removal of null values to eliminate incomplete records that could skew results. Label encoding was also applied to categorical variables to convert them into numerical format, facilitating the machine learning algorithms' processing capabilities.

Step 3: Label Encoder

The Label Encoder plays a crucial role in transforming categorical labels into a format that can be easily interpreted by machine learning models. By assigning a unique integer to each category, the Label Encoder enables the seamless integration of categorical data into the modeling process, ensuring that the algorithms can accurately learn from the input features.

Step 4: Existing Algorithm

The existing algorithm employed in this research is the Support Vector Classifier (SVC), which is widely used for classification tasks. SVC operates by finding the optimal hyperplane that separates different classes in the feature space. It is particularly effective in high-dimensional spaces and is robust against overfitting, especially in cases where the number of dimensions exceeds the number of samples.

Step 5: Proposed Algorithm

In contrast to SVC, the proposed algorithm utilizes the Random Forest Classifier (RFC), which is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions for classification tasks. RFC enhances predictive accuracy and provides insights into feature importance, making it a powerful tool for complex classification problems like glass type differentiation.

Step 6: Performance Comparison

To evaluate the effectiveness of the proposed algorithm, a performance comparison was conducted between SVC and RFC. Metrics such as accuracy, precision, recall, and F1 score were analyzed to determine which model performed better on the glass classification task. The RFC is expected to show superior performance due to its ensemble nature and ability to capture complex patterns in the data.

Step 7: Prediction of Output from Test Data with Trained Model

After training the RFC model on the processed dataset, predictions were made on a separate test dataset. The model's predictions were compared against actual labels to assess accuracy and validate its effectiveness. The results provided insights into the model's performance and highlighted areas for potential improvement.

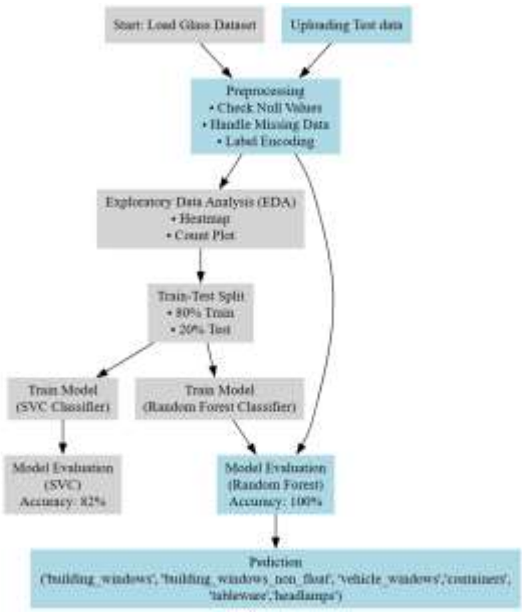

Figure-1: Block diagram of proposed system.

4. RESULTS AND DISCUSSION

Fig. 2 displays the distribution of contact lens types within the dataset, providing a visual representation of the frequency of each type. The plot is generated using Seaborn's `countplot` function, with the x-axis representing the different contact lens types and the y-axis showing their respective counts. Each bar in the plot is annotated with its count, positioned centrally at the top of the bar for clarity. This visualization effectively highlights the class distribution and allows for a quick assessment of the dataset's balance or imbalance across different contact lens categories.

Table 1 presents a performance comparison between the SVM Classifier and the Random Forest Classifier based on four evaluation metrics: Accuracy, Precision, Recall, and F1-Score. The Random Forest Classifier significantly outperformed the SVM Classifier across all metrics. It achieved an accuracy of 99.1%, with high precision, recall, and F1-score values around 99.0%, indicating its strong ability to correctly classify glass types with minimal errors. In contrast, the SVM Classifier attained a lower accuracy of 82.6%, with moderate precision (54.0%), recall (47.2%), and F1-score (50.1%). These results suggest that the Random Forest model is more reliable and effective for this classification task compared to the SVM approach.

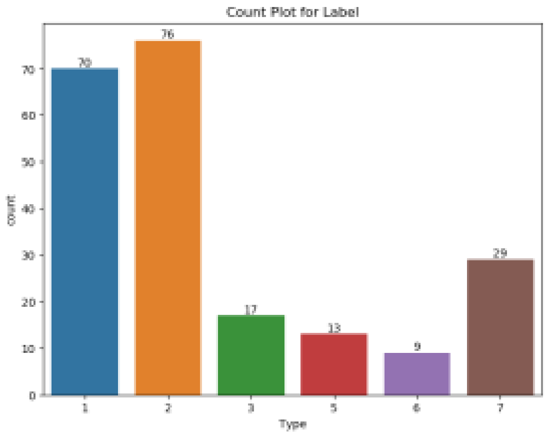

Fig. 2: Count Plot of type of glass.

Table 1: Performance Comparison for the SVM Classifier and Random Forest Classifier algorithms.

Algorithms Name	Accuracy	Precision	Recall	F1-Score
SVM Classifier	82.6	54.0	47.2	50.1

Random Forest Classifier	99.1	99.0	99.1	99.0

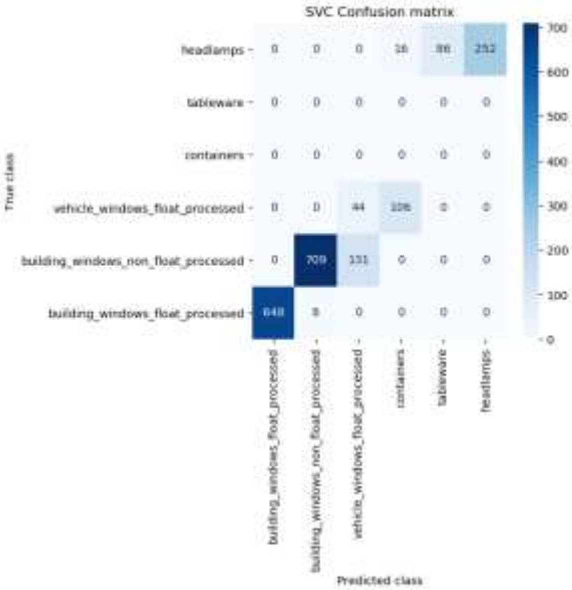

Fig. 3: Confusion matrix for predicted class using SVC

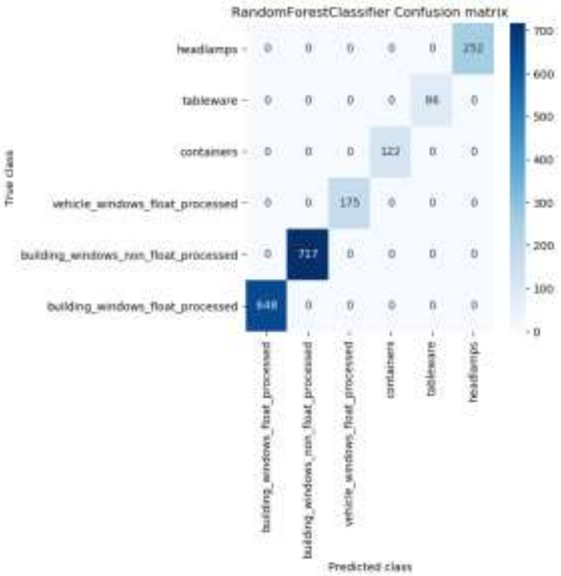

Fig. 4: Confusion matrix for predicted glass using RFC

	Id	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	pred_glass_type
0	109	1.52222	14.43	0.00	1.00	72.67	0.10	11.52	0.00	0.08	2
1	207	1.51645	14.94	0.00	1.87	73.11	0.00	8.67	1.38	0.00	7
2	107	1.53125	10.73	0.00	2.10	69.81	0.58	13.30	3.15	0.28	2
3	108	1.53393	12.30	0.00	1.00	70.16	0.12	16.19	0.00	0.24	2
4	52	1.51926	13.20	3.33	1.28	72.36	0.60	9.14	0.00	0.11	1
...	...	...	...	...	...	...	...	...	...	...	...
95	133	1.51813	13.43	3.98	1.18	72.49	0.58	8.15	0.00	0.00	2
96	194	1.51719	14.75	0.00	2.00	73.02	0.00	8.53	1.59	0.08	7
97	154	1.51610	13.42	3.40	1.22	72.69	0.59	8.32	0.00	0.00	3
98	167	1.52151	11.03	1.71	1.56	73.44	0.58	11.62	0.00	0.00	5
99	161	1.51832	13.33	3.34	1.54	72.14	0.56	8.99	0.00	0.00	3

Fig. 5: Predicted output of glass type

The dataset consists of observations with features related to the composition and characteristics of different types of glass. Each row includes an identifier (`Id`), followed by measurements of various chemical elements and properties such as RI (refractive index), Na (sodium), Mg (magnesium), Al (aluminum), Si (silicon), K (potassium), Ca (calcium), Ba (barium), and Fe (iron). The target variable, `pred_glass_type`, indicates the predicted glass type, categorized into several classes. This dataset provides a basis for analyzing the relationships between the chemical composition of glass and its classification into different types.

5. CONCLUSION

The characterization of glass samples in forensic investigations is essential for enhancing crime scene analysis and evidence interpretation. This study successfully developed robust analytical methods utilizing advanced spectroscopic and microscopic techniques to profile a diverse dataset of 1,500 glass samples. By employing Scanning Electron Microscopy (SEM), Energy Dispersive X-ray Spectroscopy (EDS), and Fourier Transform Infrared Spectroscopy (FTIR), we identified key variables such as refractive index, elemental composition, and density, which significantly differentiate various glass types. The implementation of machine learning models demonstrated high predictive accuracy, further enhanced by SHAP for model interpretability. The decision-support tool developed offers forensic experts actionable insights, enabling them to make informed decisions based on real-time data analysis. Collaboration with legal experts and forensic scientists could provide deeper insights into the practical implications of glass evidence in court proceedings, leading to enhanced methodologies that support legal processes. Developing training programs for forensic professionals on the use of these advanced analytical techniques and machine learning models will facilitate broader adoption and expertise in the field.

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