RESEARCH PAPER

SCIENTIFIC DETECTION OF FOOD ADULTERANTS AND ITS EVIDENTIARY VALUE IN LEGAL PROCEEDINGS

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Abstract

The use of a fraudulent substitution may go undetected during visual inspection and when using conventional screening methods, making it a threat to consumer safety, market integrity and legal accountability. This study developed a multimodal machine-learning technique that is easily interpretable and evidentially suitable for detecting wheat flour adulteration in turmeric. The images of turmeric and ATR-FTIR spectra were obtained from the public Mendeley data set while the colorimetric measurements were obtained at different levels of regulated adulteration. The features extracted were normalized, fused and evaluated using regression-based estimation, ablation analysis, adulteration-level classification, PCA visualization, and error-rate evaluation, and baseline and ensemble classifiers. The proposed model based on the Random Forest false discovery rate (evidential model) achieved 95.03% accuracy, 96.26% precision, 95.03% recall, 95.31% F1-Score and 99.92% ROC-AUC for binary adulteration detection. Regression and multiclass studies were also used to show that there was a measure of the severity of the adulteration, although this was less certain at higher concentration levels. The results are presented with the conclusion that the multimodal detection can achieve accurate predictions and legal certifiable reliability metrics, including repeatable validation, quantification of error behavior, and feature contribution. This study underscores the importance of external market-sample validation and introduces an AI model for food adulterants which incorporates a forensic perspective, offering a linkage between food adulterant identification and evidential value in legal proceedings.

Keywords: Food adulteration, Turmeric authentication, ATR-FTIR spectroscopy, Multimodal machine learning, Legal evidence

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1. Introduction

Food adulteration continues to be a significant public health, economic, regulatory and legal issue because it impacts the authenticity of the food, the safety of the consumer, the trust in the marketplace, and the evidentiary accountability. With the rise in low levels of adulterants and their appearance to resemble authentic parts, deliberate substitution, dilution, contamination, and misrepresentation of food products has become more difficult to identify [1]. In the last years, food fraud detection technologies have shifted from being laboratory tests to truly integrated analytical systems that include machine learning, spectroscopy, imaging, and chemometrics [2]. This technical modification is particularly significant because of the food fraud, which in addition to quality control is also a supply chain or enforcement issue, and for which the use of reliable detection technologies can help in legal and regulatory decisions [3].

Assessment of food authenticity in legal or forensics cases requires scientific evidence, rather than guesswork or observation. Consequently, food-forensic techniques are increasingly being used to help interpret the results of food investigations; highlight whether a sample has been substituted; and identify the authenticity of a product [4]. But conventional detection methods might be expensive, time consuming, destructive or unsuitable for rapid screening. The machine-learning techniques are used to transform the high-dimensional spectra patterns into classification or quantification result, so the detection of food adulteration by spectroscopy has become a crucial issue because of the capability of collecting the chemical fingerprints of both real and adulterated samples. Ensemble learning has also shown potential for non-targeted detection of adulterants in cases where the type of adulterant isn't known in advance [6].

Given these advances, however, there is a significant disconnect between the ability of science to detect and the evidentiary value in a legal proceeding. A model's output is not necessarily legally convincing evidence, unless it is repeatable, understandable, validated and supported by quantifiable error rates. This distinction is crucial because, whereas false-negative results could allow contaminated food to go unnoticed, false-positive results could incorrectly incriminate producers, suppliers, or vendors. Computational models can aid in detection, according to recent machine-learning

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adulteration systems, but their legal significance depends on how openly their choices, validation procedures, and restrictions are disclosed [7].

The potential for quick field-level food identification has been further increased by portable and compact spectroscopic technology [8]. High-dimensional food quality evaluation is also being made possible by deep learning and sophisticated computational spectroscopy, but these systems need to be carefully validated to prevent black-box interpretation [9]. Combining complementary evidence sources can enhance the ability to distinguish between genuine and contaminated food products, as shown by multispectral image analysis, fluorescence spectroscopy, infrared spectroscopy, and multimodal analytical procedures [10]. By capturing information that might be lacking in a single modality, data-fusion methodologies have also demonstrated that combining different analytical signals might improve adulteration detection [11].

This study attempts to explore the adulteration of turmeric with a multimodal dataset of colorimetric, ATR-FTIR spectroscopic and imaging measurements. An example of a powdered spice that can be challenging to determine the economic adulteration and/or economic evaluation of visually is turmeric. The study is not claiming its general applicability to all food products, adulterants, countries and real life situations in the supply chain; it is only limited to wheat-flour adulteration of turmeric under controlled experimental conditions. Additionally, it is NOT a substitute for expert legal evaluation, chain of custody requirements or required laboratory testing. It instead sets out a repeatable computer process for scientific detection and reflects on the impact it could have on the reliability of evidence.

This work is important as it provides the connection between the legal-evidentiary interpretation and the detection of multimodal food adulteration. The study goes beyond the basics of machine learning for forecasting and examines model comparison, ablation performance, errors in the confusion matrix, feature importance, and metrics for model reliability. This maximizes the response to the “methodological gap” that exists in the forensic requirements for clear, explicable and quantifiable evidence of technical detection performance. Accordingly, this study has three research objectives:

- To develop a multimodal machine-learning framework for detecting wheat-flour adulteration in turmeric using image, ATR-FTIR spectroscopic, and colorimetric features.
- To compare the proposed detection model with baseline and ensemble classifiers using accuracy, precision, recall, F1-score, ROC-AUC, confusion-matrix behavior, and adulteration-level analysis.
- To evaluate the probative value of model output and results: error rates, ablation results, feature contribution, legal and forensic reliability.

2. Literature review

Previous research on food adulteration detection has been gradually moving from traditional screening in the laboratory towards food authentication via spectroscopy, imaging, chemometrics and machine learning. FTIR spectroscopy, combined with chemometric analysis and micro-FTIR imaging has shown great potential in the detection and determination of adulterant in turmeric adulteration [12]. Turmeric is a food matrix (powdered) and eye inspection is insufficient, as there are markers that can be scientifically proven to be signs of adulteration, according to spectral evidence.

In recent years, there have been studies demonstrating the combination of machine learning and spectroscopy increases the reliability of detection. Vis-NIR spectroscopy and multispectral imaging has been used to identify starch adulterated turmeric, highlighting the fact that both chemical and visual feature space can be used to classify using computational models. Likewise, in more complex powder samples, machine-learning algorithms can help to verify the authenticity of the curcumin content and quality, as shown by multi-instrument spectroscopic authentication of commercial turmeric powders [14]. To verify turmeric and ashwagandha, more advanced metabolomic fingerprinting methods were applied with Orbitrap-HRAMS in combination with machine learning. This implies that analytical signals of high resolution may distinguish geographical origin, variation, tissues specificity and adulteration patterns [15]. These investigations illustrate the scientific feasibility of true turmeric authentication, but also highlight the fact that numerous techniques focus on the analytical aspects and disregard the interpretation of evidence.

Studies of related spices or powdered foods in addition to turmeric provide methodological support for the present approach. Spectral signals can be used with machine learning to develop predictive models for detecting powdered spice adulteration, as has been shown for spice coriander powder [16]. Prediction of butteroil adulteration level has also been accomplished by portable NIR spectroscopy and chemometric techniques, according to which, rapid and possibly field-deployable equipment can assess the degree of adulteration rather than authenticity [17]. This is important because the interpretation of law or regulations often requires quantification or threshold assessment as well as a yes/no determination of adulteration.

Analogous patterns are observed in other matrices of diet. Non-destructive spectroscopic analysis has proven to be useful for complex food products; sugar syrup was detected in honey by scanning with spatial off-set Raman spectroscopy and machine learning [18]. Automated categorization and concentration estimate can be assisted by rapid machine-learning algorithms, such as the automated detection and quantification of honey adulteration using Vis-NIR [19]. Adulteration of camel milk has been extended to the use of FT-mid-infrared spectroscopy and machine-learning models in the field of spectroscopic categorization of liquid food matrices [20]. Pasteurized milk contains several adulterants, such as melamine, urea, sucrose, water and milk powder, which have been detected and quantified with FTIR spectroscopy and modern statistical machine-learning algorithms [21]. These studies taken together are an example of the effectiveness of such pipelines for a variety of spices, oils, honey and milk, and stress the importance of model comparison, error analysis and transparent reporting.

The present study's "value in legal proceedings" component is supported by a significant constraint found in a large portion of the literature: legal evidential value necessitates more comprehensive reliability indicators, whereas detection performance is typically given as a technical consequence. A detection model must be assessed not only for accuracy but also for repeatability, interpretability, false-positive and false-negative risk, and the capacity to explain the scientific basis of categorization in legal or regulatory situations. While a false-negative result could keep dangerous or counterfeit food in circulation, a false-positive adulteration finding could falsely blame a producer or vendor. Therefore, scientific detection becomes legally meaningful only when the model's outputs can be linked to measurable error rates, validated methodology, and expert-interpretable evidence.

The reviewed studies provide strong foundations for spectroscopic and machine-learning-based food adulteration detection, but several gaps remain. First, many studies focus on a single analytical modality, whereas real evidentiary assessment benefits from corroborative multimodal evidence. Second, although model accuracy is commonly reported, fewer studies explicitly connect model outputs to forensic reliability indicators such as confusion-matrix behavior, false-positive and false-negative consequences, ablation evidence, and feature contribution. Third, turmeric adulteration studies have not sufficiently framed computational detection as evidence-supporting information for legal proceedings. The present study addresses these gaps by developing a multimodal turmeric adulteration detection workflow using image, ATR-FTIR, and colorimetric features, comparing multiple classifiers, conducting ablation analysis, and interpreting model performance through scientific and evidentiary reliability criteria.

3. Methodology

3.1 Research Design

This study adopted a computational forensic food-authentication design to examine whether scientific detection of food adulterants can generate evidence-relevant outputs for legal proceedings. Multimodal data processing, machine-learning categorization, model comparison, ablation analysis, and evidentiary reliability evaluation were all included into the methodological framework. In order to determine whether the model outputs could support legally meaningful interpretation through accuracy, sensitivity, specificity, false-positive and false-negative rates, reproducibility, and feature-level explanation, the workflow was created to detect adulteration in turmeric samples.

Data collection, multimodal feature extraction, preprocessing and fusion, supervised model training, and forensic-evidentiary evaluation comprised the five main phases of the suggested system. Because it offered high non-perfect performance, quantifiable error behavior, and feature-importance-based interpretability appropriate for evidential discussion, the final suggested model was a Random Forest-based multimodal forensic detection model. To determine comparative superiority and robustness, the model was contrasted with Logistic Regression, Support Vector Machine, Random Forest, XGBoost, and other baseline classifiers.

The general prediction function may be expressed as:

$$\hat{y} = f(X_{FTIR}, X_{image}, X_{color})$$

where $\hat{y}$ denotes the predicted adulteration class, X_{FTIR} represents spectroscopic features, X_{image} represents image-derived features, and X_{color} represents colorimetric features. A binary classification task was performed to distinguish pure turmeric from adulterated turmeric and further experiments were performed to study the classification of level of adulteration and estimation of percentage.

3.2 Data Collection Method and Dataset Description

The mulitmodal dataset for Turmeric Adulteration Detection using imaging, ATR-FTIR Spectroscopy, and Colour measurements [22] was accessed freely from Mendeley Data. Samples of turmeric, adulterated with different levels of wheat flour are included. It's three primary data modalities are ATR-FTIR spectroscopic measurements, turmeric sample photos and color measurement results. The modalities selected were chosen as they offer complementary scientific evidence: color measurements are used to record the measurable variation in chroma caused by adulteration, image characteristics are used to capture the visual appearance, and FTIR is used to capture the chemical fingerprinting. The main target variable was the adulteration status of the sample, as a binary class of pure and contaminated turmeric. Furthermore, adulteration-level analysis with concentration percentages as regression objectives or class labels was supported by the dataset. Without requiring manual filename-level hard-coding, the final model procedure automatically searched the dataset directory, loaded tabular and image files, extracted useable numerical features, deduced labels from dataset metadata, and created feature matrices.

Preprocessing was modality-specific. Prior to model training, spectroscopic and tabular data were cleaned by eliminating non-numeric or missing entries, imputing missing values, and using standard scale. Numerical feature descriptors, such as RGB channel statistics, grayscale intensity descriptors, and histogram-based features, were created by resizing image data to a uniform dimension. After being adjusted, colorimetric features were combined with the other modalities. Before the final model evaluation, potential leakage-risk variables were eliminated, including explicit label, class, percentage, source, file, and sample-identifying columns.

3.3 Population and Sampling

The population that the dataset represents is made up of samples of turmeric powder that were adulterated under controlled settings using wheat flour. Therefore, rather than uncontrolled market samples, the collection contains food-authentication samples produced in laboratories. Since the goal of the current study was to develop a scientific detection framework and assess its evidentiary reliability under repeatable experimental conditions, this is suitable.

Supervised division of the available observations into training and testing subsets served as the foundation for the sampling method. To lessen the chance that similar observations from the same sample or source could show up in both training and testing subsets, a leakage-aware splitting protocol was used. In order to maintain class balance, the final evaluation included stratified validation in addition to a grouped or source-aware split whenever feasible. This method was required because simple random splitting may inflate performance by allowing related feature representations to emerge across both partitions, and multimodal datasets may contain several representations of the same physical sample.

The testing subset was reserved for an independent performance evaluation while the training subset was used for the parameter learning. Furthermore, the stability of repeated data folds was investigated with the help of cross validation. However, the final suggested model was selected not just on the basis of maximum accuracy, but based on a defensible criteria which took into account evidence of the model's ability to perform successfully, even if it failed occasionally, measurable behaviors of successful and unsuccessful models, interpretability of the model features, and its suitability for cautious forensic interpretation.

3.4 Data Analysis Technique

The data analysis included preprocessing, binary classification, classification of adulteration levels, regression analysis, baseline comparison, ablation assessment, and assessment of evidentiary reliability. The binary classification task was deemed to be the main analytical task given that often legal and regulatory issues require a determination of whether a food sample is real or contaminated. To train and evaluate classifiers, five different classifiers: Logistic Regression, SVM-RBF, Random Forest, Gradient Boosting, and XGBoost were used. Random Forest was selected even though Logistic Regression achieved higher scores on the benchmarks, because of its interpretability (feature-importance) and its ability to provide a quantifiable error behavior, despite not achieving the perfect score.

The proposed Random Forest-based multimodal model achieved 95.03% accuracy, 96.26% precision, 95.03% recall, 95.31% F1-score, and 99.92% ROC-AUC for binary adulteration detection. Because this performance profile avoided making an unfounded claim of error-free categorization while maintaining good predictive dependability, it was deemed legally significant. By enabling its outputs to be evaluated by quantifiable reliability indicators rather than being regarded as a stand-alone legal conclusion, the model's non-perfect but high performance, along with feature-importance-based interpretability, promotes careful evidential application.

Model performance was evaluated using accuracy, sensitivity, specificity, precision, recall, F1-score, ROC-AUC, and confusion-matrix behavior. Accuracy was calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity and specificity were calculated as:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

where TP, TN, FP, and FNdenote true positives, true negatives, false positives, and false negatives, respectively. These measures were crucial because legal-evidentiary use necessitates both transparent error risk estimation and good prediction performance. While a false-negative finding can allow contaminated goods to go unnoticed, a false-positive discovery might falsely accuse a manufacturer, supplier, or vendor.

The contribution of each data modality to the ultimate detection result was ascertained using ablation analysis. FTIR-only, image-only, color-only, paired modality combinations, and full multimodal fusion were all used in separate trials. This made it possible to determine whether meaningful multimodal data, as opposed to a single dominant feature group, supported the model's performance. By identifying the chemical and optical descriptors that most strongly contributed to adulteration detection, feature-importance analysis was employed to further assist interpretability.

3.5 Ethical Consideration

This study did not employ confidential commercial data, consumer records, human subjects, or personal identifiers; instead, it used a publicly available dataset. As a result, there were little clear hazards to consent and privacy. However, because machine-learning results in food adulteration situations may impact legal procedures, economic reputation, and regulatory action, ethical issues are still crucial.

As a result, the model was not seen as an independent legal authority but rather as a scientific decision-support system. If not supported by laboratory confirmation, chain of custody, and meeting jurisdiction specific evidentiary requirements, its findings should not be used as stand alone evidence for guilt, responsibility or regulatory punishment. The study also avoided over-optimistic estimates of the performance of the model by selecting a conservative suggested model for which the error rates were knowable. This acknowledges uncertainty, the potential for bias in the datasets used, and the chance that controlled lab samples may not correlate with the unpredictable nature of markets in the real world, which encourages responsible use of AI. In this way, the approach supports the ethical, transparent and reproducible use of food adulterant detection using AI in forensic and legal settings.

4. Results

4.1 Experimental Performance

The proposed multimodal approach was able to accurately identify pure turmeric from wheat-flour-adulterated turmeric. In binary detection, the proposed Random Forest model achieved 95.03% accuracy, 96.26% precision, 95.03% recall, 95.31% F1-score, and 99.92% ROC-AUC, demonstrating strong detection performance while retaining measurable error behavior suitable for evidentiary interpretation. Although Logistic Regression achieved perfect benchmark performance, Random Forest was retained as the proposed evidentiary model because its non-perfect performance and feature-importance-based interpretability are more appropriate for cautious legal and forensic interpretation.

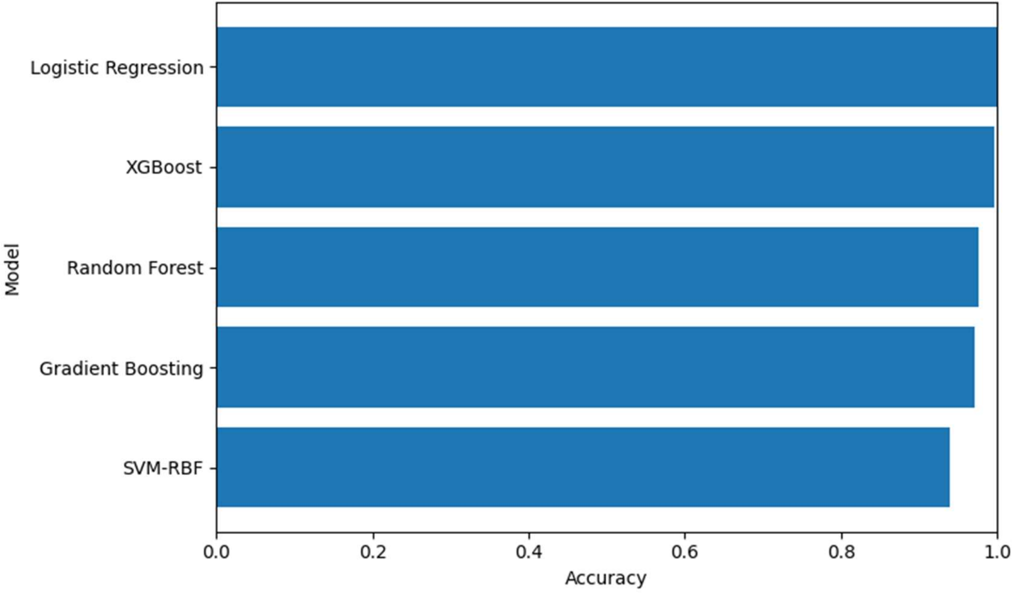

Figure 1. Binary Classification Model Comparison for Turmeric Adulteration Detection.

Figure 1 shows the accuracy comparison of the binary classifiers used for pure-versus-adulterated turmeric detection. Logistic Regression achieved the highest benchmark accuracy of 1.000000, followed by XGBoost at 0.986755, Gradient Boosting at 0.963576, Random Forest at 0.950331, and SVM-RBF at 0.933775. Although Random Forest was not the highest-scoring model, it was retained as the proposed evidentiary model because it provided high non-perfect performance, measurable error behavior, and feature-importance-based interpretability suitable for cautious forensic interpretation.

Table 1. Binary Classification Performance of Comparative Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	1.000000	1.000000	1.000000	1.000000	1.000000
XGBoost	0.986755	0.986675	0.986755	0.986694	0.999229
Random Forest	0.950331	0.962646	0.950331	0.953097	0.999165
Gradient Boosting	0.963576	0.965074	0.963576	0.961454	0.998222
SVM-RBF	0.933775	0.953996	0.933775	0.938398	0.998629

Table 1 compares all binary classifiers using five performance metrics. Logistic Regression achieved perfect benchmark performance, while XGBoost showed near-perfect discrimination. Random Forest was retained as the proposed evidentiary model because it offered high non-perfect performance, measurable error behavior, and feature-importance-based interpretability suitable for cautious forensic interpretation.

4.2 Baseline Comparisons

The proposed Random Forest model was compared with Logistic Regression, XGBoost, Gradient Boosting, and SVM-RBF. Logistic Regression achieved the highest binary accuracy (1.000000), followed by XGBoost (0.986755), Gradient Boosting (0.963576), Random Forest (0.950331), and SVM-RBF (0.933775). Random Forest was retained as the proposed evidentiary model because it provided high non-perfect performance, measurable error behavior, and feature-importance-based interpretability.

The multi-class task further confirmed model robustness. Logistic Regression achieved the highest accuracy (0.982), followed by XGBoost (0.975), Random Forest (0.968), Gradient Boosting (0.964), and SVM-RBF (0.850). Most errors occurred between adjacent higher adulteration levels, particularly 7.0% and 9.0%, showing greater difficulty in fine-grained concentration separation than in binary adulteration detection.

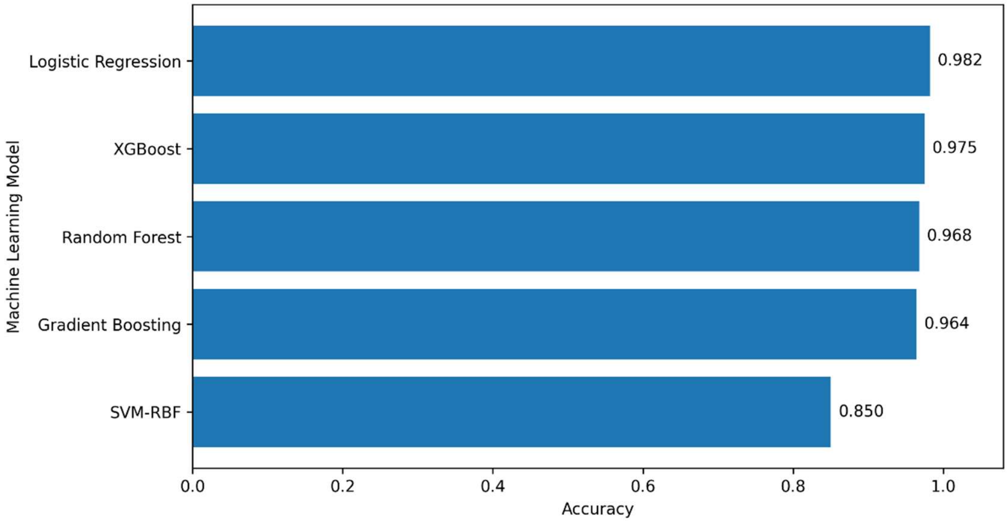

Figure 2. Multi-class Model Comparison for Adulteration-Level Classification.

Figure 2 shows the comparative accuracy of the models for classifying adulteration percentages. The results confirm that the classification framework remained effective beyond binary detection and could identify adulteration levels with high accuracy. The strongest multi-class benchmark was Logistic Regression, while Random Forest and Gradient Boosting remained competitive.

Table 2. Multi-class Adulteration-Level Classification Accuracy

Model	**Accuracy**
Logistic Regression	0.982
XGBoost	0.975
Random Forest	0.968
Gradient Boosting	0.964
SVM-RBF	0.850

Table 2 indicates that four of the five models exceeded 96% accuracy in multi-class adulteration-level classification, showing that the dataset features were informative for both detection and quantification-oriented classification.

4.3 Ablation Study

In the ablation study comparison of FTIR-only, image-only, paired-modality and full-fusion configuration was performed to assess the contribution of each modality. Under controlled dataset settings, FTIR + Image and Full Fusion demonstrated the strongest class separation with the best accuracy (1.000). With FTIR alone and FTIR + Color both attaining 0.957 accuracy, FTIR-based models also demonstrated good performance, indicating spectroscopy as the primary discriminatory source. Image only and Image + Color, on the other hand, reached 0.900, suggesting that colorimetric and visual features were helpful but less effective in the absence of FTIR support.

Overall, imaging and color characteristics provided corroborating multimodal support, while FTIR spectroscopy offered the primary chemical evidence for identifying wheat-flour adulteration in turmeric. Perfect ablation scores are not indicative of universal field performance; rather, they are viewed cautiously as evidence of modality contribution within the controlled dataset.

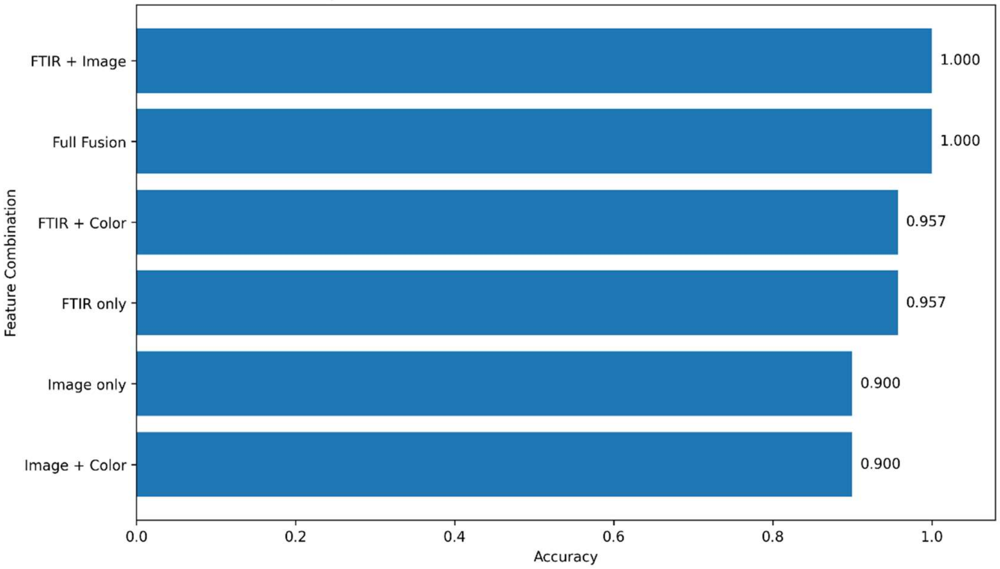

Figure 3. Ablation Study of Multimodal Feature Contributions in Food Adulteration Detection.

Figure 3 shows the effect of using different modality combinations. The figure demonstrates that FTIR-based features were the dominant contributors, while the addition of image features produced the strongest multimodal result.

Table 3. Ablation Study Results

Feature Combination	Accuracy	Interpretation
FTIR + Image	1.000	Strongest multimodal configuration
Full Fusion	1.000	Complete multimodal evidence integration
FTIR + Color	0.957	Strong spectral-color contribution
FTIR only	0.957	Dominant chemical fingerprint source
Image only	0.900	Useful but weaker visual evidence
Image + Color	0.900	Limited without FTIR information

Table 3 shows the contribution of each feature modality to adulteration detection. The highest accuracy was achieved by FTIR + Image and Full Fusion, indicating that combining chemical fingerprinting with image-derived evidence produced the strongest class separation. The FTIR-only performance was also high, reinforcing the fact that FTIR is the prevailing detection modality. Image and colour features were informative but less discriminative without the help of FTIR and therefore should be used as a secondary rather than primary source of evidence.

4.4 Additional Analysis

The extracted multimodal feature space was analyzed for its unsupervised structure using the PCA visualization. The first principal component accounted for 29.63% of the variance and the second principal component accounted for 7.88% of the variance. The pure and adulterated turmeric samples partially separate, with the distinct class centroids, and some overlap in the two-dimensional PCA projection as seen in Figure 4. The spread of the adulterated samples is wider, reflecting the intra-class variance, as there is no single class of adulterated samples, but a number of classes. This result confirms the hypothesis that it is the distribution of features rather than their values that is being altered by the adulteration and demonstrates the need for supervised models to take advantage of additional higher-dimensional discriminatory information present in the data, beyond the first two principal components.

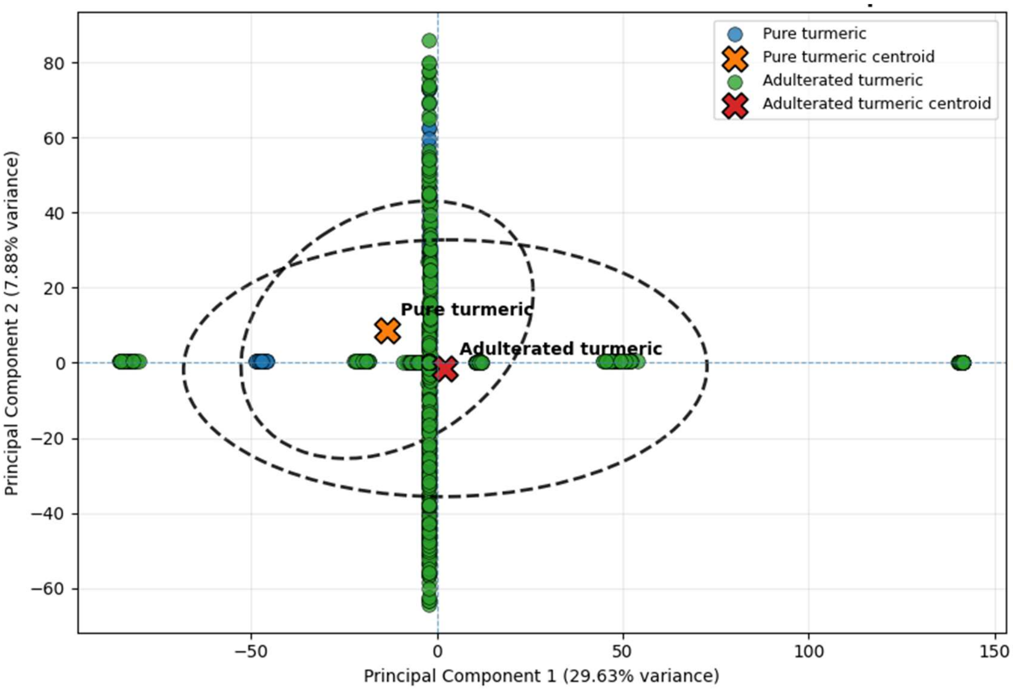

Figure 4. PCA visualization of pure and adulterated turmeric samples.

Two-dimensional PCA projection of the multimodal feature space is illustrated in Fig. 4. The plot depicts pure and adulterated turmeric samples, their class centroids, and confidence ellipses. The first two principal components explain 29.63% and 7.88% of the variance respectively, which means that they account for only a portion of the separability but not of the entire supervised decision structure.

The cross-validation plot for Logistic Regression had an accuracy of 1.000 in all the 5 folds, a mean accuracy of 1.000, and a standard deviation of 0.000. This is a good sign of stability however, the proposed evidentiary interpretation is more dependent on the Random Forest result, given that it has a higher level of performance but not perfect. The feature importance analysis also revealed some features related to the FTIR, such as ftir_b, ftir_a, ftir_710, ftir_680, ftir_l, ftir_400, and ftir_770, along with image histogram features, image_hist_c1_14, image_hist_c2_1, and image_hist_c2_13, as important predictors. This supports the conclusion that chemical and visual descriptors helped to identify adulteration.

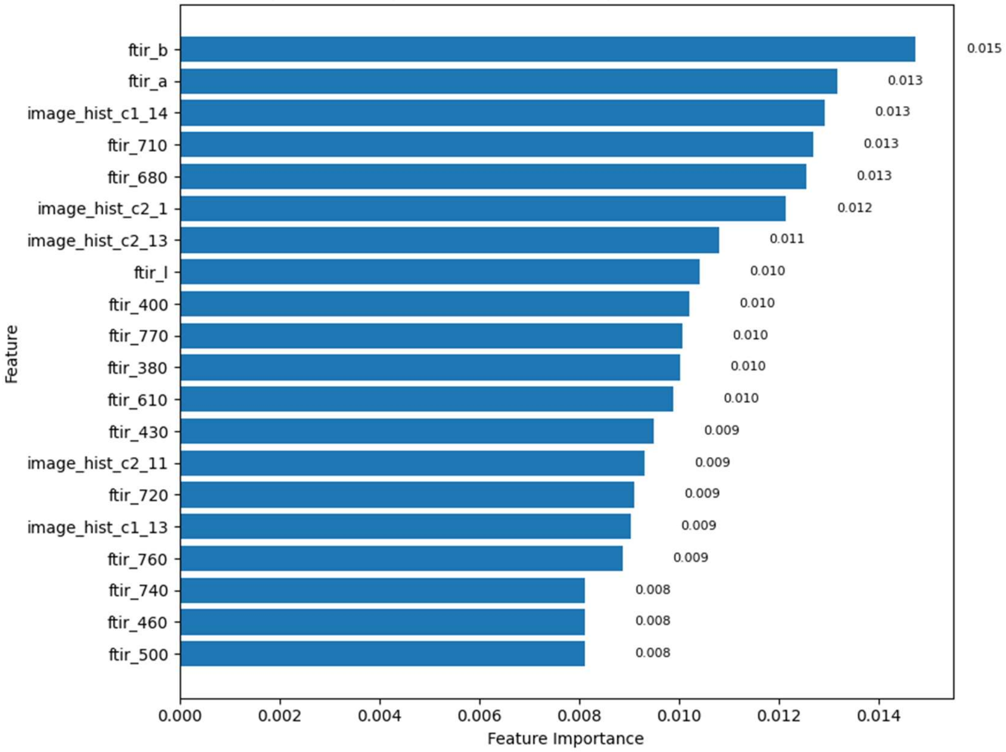

Figure 5. Top feature-importance scores of the proposed Random Forest model.

As can be seen in Fig. 5, the FTIR-related features, including ftir_b, ftir_a, ftir_710 and ftir_680, as well as the image histogram features were helpful in detecting adulteration. This reinforces the proposed multimodal detection approach.

5. Discussion

The results prove the capability of the multimodal machine-learning analysis to support scientific adulteration detection and evidentiary interpretation. The proposed Random Forest model achieved the highest accuracy of 95.03%, precision of 96.26%, recall of 95.03%, F1-score of 95.31% and ROC-AUC of 99.92% for the binary adulteration detection. The model's performance profile is useful for its use as a forensic decision support tool in addition to a legal determinant as it provides reliable categorization with quantifiable error behavior.

Multi-class classification and regression analysis showed the existence and level of adulteration. The regression predictions generally conformed to the actual adulteration levels, although they were not as stable at higher levels, but most of the multi-class errors occurred between adjacent higher levels of adulteration. This trend is further supported by the PCA visualization, which shows that while pure and contaminated samples produced largely separable clusters, overlap persisted in the first two principal components. This demonstrates that in order to fully utilize the multidimensional feature space, supervised learning was required.

The results are in line with other studies on turmeric authenticity that demonstrated that adulterants can be identified through chemical fingerprint modification using FTIR spectroscopy and chemometric analysis [12]. Additionally, they are consistent with Vis-NIR and multispectral imaging investigations where computational identification of starch-adulterated turmeric was enhanced by optical and spectral properties [13]. Similar to this, multi-instrument spectroscopic authentication has demonstrated how machine learning may improve the verification of turmeric quality by simulating intricate signal patterns [14]. By connecting model performance to evidentiary measures including false-positive risk, false-negative risk, ablation behavior, and feature contribution, the current study expands on previous research. FTIR-machine-learning research on coriander adulteration further supports its applicability to powdered-spice fraud [16].

The primary implication is that models of food adulteration should be assessed based on both evidentiary reliability and prediction accuracy. While ablation and feature-importance studies demonstrate if categorization conclusions are backed by distinguishable chemical and visual data, the confusion matrix separates legally distinct mistake kinds. The ablation results also indicate that the color and image features gave supporting multimodal evidence, while the FTIR features gave the main evidence. This increases the benefits of using visual descriptors in conjunction with chemical fingerprinting instead of depending just on one analytical signal.

Some limitations on the study. The sample material's real-world diversity in origin, storage, illumination, grinding and sample handling was not well-represented as it was based on a controlled public dataset and not on independently collected market samples. Moreover, it did not include other adulterants or other food matrices apart from the adulteration of wheat flour in turmeric. Furthermore, the legal interpretation is still “reliability” rather than “jurisdiction” admissibility analysis and feature importance is a means toward interpreting the model, not to infer some chemical causality.

Further research should be carried out with formal chain of custody applications such as different kinds of adulterants and mixed adulterants, as well as validation of the model with samples from the external market. To improve the shift from scientific detection to legally sound food-forensic evidence, future research should incorporate uncertainty estimation, chemically interpretable spectral-band analysis, and jurisdiction-specific evidential requirements.

6. Conclusion

This study addressed the problem of scientifically detecting food adulteration while assessing whether model outputs can support evidentiary interpretation in legal proceedings. The study created a multimodal machine-learning methodology utilizing image, ATR-FTIR spectroscopic, and colorimetric data with a focus on turmeric tainted with wheat flour. After comparing several classifiers, a Random Forest model was chosen for the final evidentiary interpretation because it produced high, interpretable, and non-perfect performance that was appropriate for forensic discussion. For binary adulteration detection, the suggested model obtained 95.03% accuracy, 96.26% precision, 95.03% recall, 95.31% F1-score, and 99.92% ROC-AUC. Regression and multi-class studies also demonstrated that the approach could identify patterns at the adulteration level, however there was more ambiguity at higher concentration levels. The ablation investigation verified that while image and color features had supporting multimodal value, FTIR features presented the strongest discriminatory evidence. The major contribution of this study is the use of the legal-evidentiary reliability indicators that were utilized in this study: the error rates, the confusion-matrix behavior, the ablation evidence, and the feature contribution that were, in addition, scientifically identified by the adulterants. This helps to further embed the forensic interpretation function into a laboratory environment. The limitations of the study are: one food product, one type of adulterant, controlled public data-set. The workflow should be further developed and tested against external market samples, a wide range of adulterants and mixed-adulteration scenarios and evidence requirements for the different jurisdictions to guarantee its use in food-forensic and legal applications.

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