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Research Article

Identification of Spices and their Adulterants by Integrating Machine Learning and Analytical Techniques: A Representative Study

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ABSTRACT

This multidisciplinary research presents a comprehensive method to tackle the widespread problem of spice adulteration, which represents substantial risks to both public health and spice authenticity. A comprehensive approach is developed to authenticate spices with high accuracy and efficiency by combining old methods with contemporary approaches such as machine learning and artificial intelligence. This paper presents a specific case study where machine learning models, specifically using transfer learning with proven frameworks like MobileNetV2, were effectively employed. The models achieved an impressive accuracy of 98.67% in identifying *Capsicum annum*, a spice that is usually adulterated in the market. In addition, a wide range of traditional and advanced techniques, including qualitative testing, microscopy, colorimetry, density measurement, and spectroscopy, are reviewed closely. In addition, this article provides a detailed explanation of high-performance liquid chromatography (HPLC) based quantitation of capsaicin, which is the main active constituent for ascertaining the quality of *C. annum*. The present work defines a new interdisciplinary approach and also provides valuable information on evaluating the quality of spices and identifying adulterants using artificial intelligence. The outcomes presented here have the potential to completely transform the methods used to verify the authenticity of spices and herbal drugs, therefore ensuring the safety and health of consumers by confirming the quality.

Introduction

The adulteration of spices is a deceptive and unethical practice that has long been a problem in the food sector. It poses serious risks to public health and undermines the authenticity of culinary traditions. Spices, highly prized for their fragrant and taste-enhancing qualities, have a significant impact on international culinary traditions. However, the extensive adulteration of these vital components has sparked worries over the safety and genuineness of the food we eat. Adulteration is the act of adding low-quality or toxic compounds to spices, often done for financial reasons.[1-3] Typical contaminants include of additives like sawdust, starch, and chalk, as well as synthetic pigments, chemical substances and substitutes. The main motive for spice adulteration is the pursuit of financial gain by dishonest dealers and producers. Adulterating spices enables the augmentation of product amount while minimizing manufacturing expenses, hence optimizing earnings. The complex networks of suppliers engaged in spice manufacturing, together with insufficient regulatory supervision in some areas, provide an opportunity for dishonest individuals to participate in fraudulent activities without incurring immediate repercussions.[4,5]

Authenticating spices to prevent adulteration is a crucial element in guaranteeing the quality and safety of these indispensable culinary components. Diverse ways are used to authenticate the genuineness of spices, encompassing both conventional approaches and cutting-edge technology. Moreover, chemical analysis methods

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like chromatography and spectroscopy are used to ascertain the presence of certain components, therefore verifying that the spice composition adheres to defined criteria.[6,7] Although these procedures are somewhat successful, they are not without disadvantages. Several conventional authentication procedures are characterized by being time-consuming, requiring a significant amount of effort, and perhaps lacking the necessary accuracy to identify slight adulteration. In addition to time consuming traditional method and costly chemical analysis method, there is lack of digital identification of spices and their adulterants presents difficulties for testing and authentication approaches.[8-10]

Machine learning (ML) models and artificial intelligence (AI) are highly advanced technologies that are significantly transforming different sectors and parts of our everyday life. ML, a subfield of AI, enables computers to acquire knowledge from data, identify patterns, and make informed judgments without the need for explicit programming.[11,12] This revolutionary technology has a wide range of applications, including picture and voice recognition, predictive analytics, and autonomous systems. AI, in contrast, spans a wider range of talents, with the goal of endowing robots with intellect that resembles that of humans. In this digital age, the incorporation of ML models and AI has become crucial for addressing intricate challenges, enhancing processes, and extracting unparalleled insights from extensive datasets.

Integration of ML Models in the Area of Authentication of Spices

Utilizing ML models for spice authentication has great potential in combating adulteration. ML provides a sophisticated method for spice authentication by using its capacity to analyze large datasets and detect complex patterns. These models may be trained using extensive datasets that include the chemical profiles, physical features, and sensory aspects of real spices. ML algorithms can detect abnormalities that may suggest adulteration by understanding the intricate links among these datasets. These are very effective in rapidly and precisely analyzing and understanding this information. Moreover, the inherent adaptability of machine learning enables these models to consistently develop and enhance their precision over time, making them highly suitable for tackling the ever-changing and developing strategies used in spice adulteration.[13] Notwithstanding these benefits, there are ongoing difficulties, such as the need for varied and inclusive datasets, the comprehensibility of ML results, and the possibility of overfitting. Moreover, the use of ML models in spice authentication requires significant computing resources and knowledge, which may provide obstacles for smaller manufacturers. However, the continuous research and partnerships among the food sector, regulatory agencies, and ML specialists show great potential in creating reliable, user-friendly, and affordable ML-based authentication solutions. These technologies may improve the accuracy of spice identification and transform efforts to combat adulteration by offering real-time monitoring and adaptable solutions to guarantee the integrity and safety of spice supply chains. ML's progress provides a potent tool to safeguard customers from contaminated spices, while also upholding the cultural and culinary legacy tied to these vital components.[7]

Research Gaps and Motivations

In the Indian context, our research team has conceptualized the application of deep learning and artificial intelligence based methodologies for identification and authentication of herbal drugs and spices and suggested a robust computational approach for the same.[7] Similarly, the concept was discussed in relation to the present state of art and relevant literature and it was proposed that machine learning and artificial intelligence-based techniques can be a suitable alternative for the traditional practice of knowledge-based identification of herbs and spices. This chapter explains the several models that were used, such as the transfer model, and provides a detailed description of the procedural stages involved in developing the model. Furthermore, it also explains the different parameters that help in evaluating the performance of the developed model.[13] Later on, the proposed methodology was tested on ML-based identification of selected spices and their biological adulterants. In one of the previous study, we compared three transfer learning models, MobileNet, VGG19, and Inception V3, for the identification of cardamom and its adulterants. Our group achieved an impressive accuracy of 97.5% in identification. This study paves the way for further research, including the identification of other spices and their adulterants using ML models.[14] Based upon our initial investigation, our team also proceeded to use the CNN-MobileNet V2 transfer model for the purpose of identifying *C. annum.* Using this methodology, impressive accuracy was achieved on small dataset. [15] More studies have focused on the advancement of ML models for the purpose of plant identification, and these studies are outlined here. Sun *et al.* created a smartphone app that use deep learning to accurately identify herbs, with a specific emphasis on streamlining the process and making herbal therapy more accessible.[16] Singh and Kaur used image recognition and ML techniques to accurately identify herbal plants by analyzing their leaf characteristics.[17] Kumar *et al.* developed an intelligent system that utilizes internet of things (IoT) and ML approaches to classify Indian medicinal plants in real-time.[18] Almazaydeh successfully obtained a high level of accuracy in identifying herbal plants by using pattern recognition and computer vision techniques.[19] Dong used image segmentation and deep learning (DL) techniques to classify Chinese herbal medicine plants.[20] Abdollahi used CNN-based techniques for identifying medicinal plants, emphasizing biodiversity preservation[21] Lozada and co-workers investigated the effectiveness of image filters for plant identification,[22] while Gao proposed a detached feature extraction strategy for traditional Chinese medicine formulas.[23] Chen *et al.* developed an auto ML model for the identification of 315 traditional herbs.[24] With the analysis of the above previous research, it has been very clear that many research happened till now has been focussed primarily on the basis of identification of plants on the basis of leaf structure while very few research has been done in the area of the identification of the raw herbs and spices.

The investigation of the feasibility of using ML algorithms for spice authentication is a developing area with several significant research gaps. There is a significant research vacuum in the field of spice authentication about the need for studies that examine the interpretability and explainability of ML models. Gaining insight into the methodology behind these models is essential for establishing confidence and promoting the use of such technologies in the spice sector. A notable deficiency exists in the limited availability of extensive and varied datasets particularly designed for training ML algorithms in the field of spice authentication. Furthermore, there is a lack of research that specifically investigates the capacity to expand and practically deploy ML models for spice authentication, particularly for small and medium-sized firms in the spice market. Smaller manufacturers may face obstacles due to the demanding processing needs and specialized knowledge required for building and maintaining ML systems.

Major Contribution of the Research Paper

By taking lead from the available reports and prior arts related to pharmacognostical and analytical standards, our group has developed a convolutional neural network (CNN) based ML model for a few commercial important spices such as *Foeniculum vulgare*, *Cuminum cyminum, Piper nigrum, Curcuma longa, Elettaria cardamom,* and *Capsicum annum;* and have found the prediction accuracy of more than 90% with ability to distinguish between the majorly employed substituents/adulterants of herbal drugs from authentic spice.

The study overviewed in this article provides a platform to explore and make substantial advancements in the areas of spice identification and to check adulterations for health and commercial benefits. The creation of an ML model for identifying spices. *C. annum* in this case, as a representative study using a CNN-MobileNetV2 architecture, demonstrates how modern advancements may be used to solve practical problems in the spice sector. The study presents a comprehensive overview for developing ML models and offers practical guidance on detecting common adulterants using simple procedures that may be done at home. Moreover, a quick and dependable HPLC technique for measuring capsaicin levels in capsicum varieties is reported which provides a helpful means for identifying better-quality varietals based on their level of spiciness. Hence it is strongly felt that the integration of these diverse approaches will enhance the entire quality control, authentication, and selection of premium quality spices in the market.

The outcomes of this research are very promising in the present pharmaceutical industry, where there is a strong emphasis on the need for high-quality and pure components. The authentication of herbal drugs and spices may be improved by combining ML, AI, and traditional methods. This not only guarantees the authenticity of pharmaceutical products containing herbs/spices and their extracts but also reduces potential health hazards associated with adulterated herbs. Furthermore, the accurate measurement of active substances such as capsaicin, made possible by techniques such as high-performance liquid chromatography (HPLC), plays a role in creating pharmaceutical products that are standardized and consistently effective. Therefore, this multidisciplinary approach has the potential to strengthen the pharmaceutical industry's efforts in guaranteeing the safety, effectiveness, and genuineness of medicinal treatments made from herb/spice-based ingredients.

Material and Methods

ML Model for Spice Identification: The Proposed Way Forward

The current scenario of interdisciplinary research through the cross-sectional interplay between the various spectrum of scientific advancement, it is very much required to look out for new alternative technologies resulting form the integration of the prior art in all disciplines for, e.g., in the case of authentication and quality control, it is essential to understand pharmacognostical investigation quantitative and qualitative analytical methodologies and ML/AI based models in relation to the spice morphology, chemical composition, and unique features based decision-making modules for the comprehensive integration. On these lines, the suggestive methodology for spice identification is shown in Fig.1.

The development of an ML model for spice identification entails a methodical procedure that includes data collection, data pre-processing, selecting a suitable model, training the selected model, and evaluating its performance. Furthermore, the use of transfer learning, which involves using pre-trained models such as VGG19, MobileNet, AlexNet, VGG16, ResNet etc. may greatly improve the effectiveness of the model.[25,26]

The stepwise illustration of ML-based decision-making module development is given below:

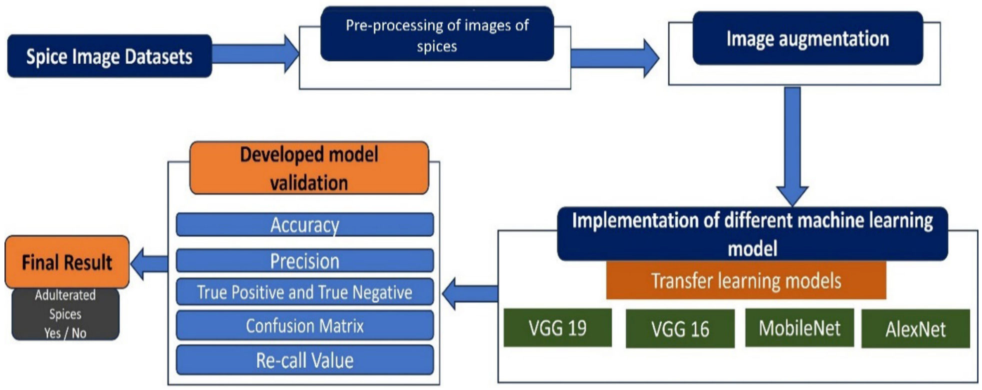


Fig. 1: The possible approach for the identification of spices using the ML methodologies

Data Collection

The first stage in constructing an ML model for spice identification involves obtaining a varied and inclusive dataset that accurately represents the subject matter. The collection should have diverse photos of selected spices, including the nuances in their visual attributes such as look, color, and texture. Researchers may amass a significant dataset by working together with integrating with all the stakeholders to get the various sample of different spices and their adulterants. The model's resilience is enhanced by the inclusion of high-resolution photos taken under diverse situations including white background and in natural condition.[27–30]

Data Pre-processing

After collecting the dataset, it is essential to pre-process the data to improve its quality and make it ready for model training. This process includes adjusting the size of images to a uniform resolution, standardizing pixel values, and enhancing the dataset via methods such as rotation, flipping, and zooming. Data augmentation enhances the model's ability to generalize across diverse variances in spice images and mitigates the risk of overfitting.[31]

Model Selection

Selecting a suitable model architecture is a crucial step in the development of an ML-based model for spice identification. Transfer learning a method in which a pre-existing model can be explored as a favored foundation. Pre-trained models such as VGG19, MobileNet, AlexNet, VGG16, ResNet etc. which have been trained on large datasets like ImageNet, etc may capture general characteristics and can be further adjusted for the purpose of identifying spices. These structures provide a harmonious equilibrium between precision and computing efficacy.[32,33]

Transfer Learning

Transfer learning is using the information acquired from addressing a particular problem (such as ImageNet classification) and employing it to address a distinct but interconnected challenge (such as spice identification). The pre-trained model is then fine-tuned to identify specific characteristics related to spices, hence accelerating the training process and necessitating a smaller dataset. The pre-trained model's layers may be immobilized, and more layers can be included to fine-tune the model for the precise purpose of spice recognition.[26,34-37]

Customizing Model Architecture

In order to validate the pre-trained model for spice detection, more layers are included in the existing architecture. The addition of these extra layers helps the model in acquiring spice-specific characteristics during the fine-tuning procedure. The output layer is modified to align with the number of spice classes present in the dataset. The architectural customization enables the model to specialize in discerning between spices and their different adulterants.

Training the Model

Once the dataset is prepared and the model architecture is determined, the training phase begins. The model is provided with spice images that have been labeled, and the weights are modified throughout each epoch (cycle of training of model) to reduce the discrepancy between the predicted and actual labels. The training procedure consists of many epochs, during which the model's performance is evaluated by monitoring measures such as accuracy and loss.

Hyperparameter Tuning

Optimizing the performance of the model requires making precise adjustments to hyperparameters, such as the learning rate, batch size, and regularization parameters. Hyperparameter tuning is an iterative procedure that involves experimenting with various settings to get optimal outcomes. It is crucial to achieve a harmonious equilibrium between the intricacy of a model and the occurrence of overfitting.

Model Evaluation

Following the training process, it is necessary to assess the performance of the model using a distinct test dataset that has not been seen before. This stage offers an impartial evaluation of the model's ability to generalize. Metrics such as accuracy, precision, recall, and F1 score are often used to assess the model's efficacy in distinguishing various spices.[38,39]

Refinement and Iteration

Depending on the evaluation outcomes, it may be essential to refine and iterate the process. Modifications to the model architecture, hyperparameters, or data preparation may be implemented to enhance performance. This iterative approach continues until the model attains appropriate outcomes on the test dataset. To summarize, the process of constructing an ML model for spice identification requires a thorough and extensive series of steps, including data collection, pre-processing, model selection, transfer learning, modification, training, assessment, and deployment. By using transfer learning approaches, such as leveraging pre-trained models, the development process is made more efficient and the model's accuracy in recognizing various spices is improved. By following this methodical approach, we may develop a strong and effective model for identifying spices that has the ability to be used in practical situations within the spice industry.

Results

Representative Study: *C. annum*

Development of ML ML-based digital model for the identification of C. annum

Recently, an ML model based on the CNN architecture with MobileNetV2 serving as a transfer learning approach for the identification of the *C. annum* was developed. Various steps involved viz. collection of data, model construction and performance assessment of CNN MobileNetV2 model, are described below as case study.

Datasets generation

For this, images of selected spices were acquired in several formats, including PNG, JPG, and JPEG, with a range of mobile phones and cameras having varied resolutions. The dataset of 20000 photos was constructed by taking photos in a specific laboratory setting with a white backdrop. Data augmentation methods, such as rotation, scaling, cropping, and noise addition, were used to improve the dataset's accuracy. Supplementary photos of possible adulterants of *C. annum* were used to construct a confusion matrix for assessing the model's effectiveness. Representative dataset containg the images of *C. annum* has been displayed as Fig. 2.

Fig. 2: Representative *C. annum* images from the developed database

Image pre-processing and splitting

To maintain consistency in data quality, all images were standardized to a resolution of 128 × 128 pixels. The dataset was partitioned into training and validation sets using a stratified 70:30 ratio to ensure an equitable distribution of various classes.

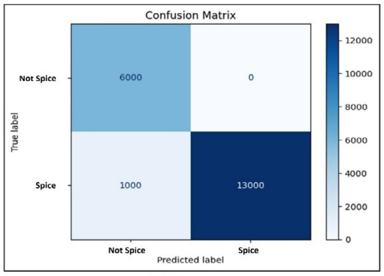
CNN-transfer learning approach

For this MobileNetV2 model as feature extractor was applied for the fine-tuning the layer-to-layer integration in order to facilitate task-specific learning, including both trainable and non-trainable parameters. The developed model exhibited an accuracy rate of 98.69%, a recall rate of 0.99, and an F1-score of 0.98. Throughout numerous epochs, the model exhibited an improvement in its performance as validated accuracy peaked at 99.7% during the 14th epoch, demonstrating significant learning.

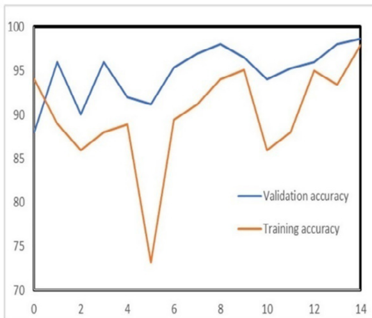
Confusion matrix

The confusion matrix displays the model's classification outcomes, with 13000 accurate classifications of the selected spice and 6000 accurate classifications of "Not spice" (as shown in Fig. 3a). There were several misclassifications observed, suggesting areas that may be improved. Developed CNN-MobileNetV2 model demonstrated exceptional performance in accurately recognizing *C. annum*, providing reliable and precise classification capabilities. The model exhibited a remarkable accuracy of 98.69%, (shown in Fig. 3b) showcasing its potential for real-world applications in spice detection. The case study emphasizes the significance of using deep learning for spice identification, which opens up possibilities for future applications in verifying and guaranteeing the quality of spices in the market.

As discussed earlier, there are very few research related to raw spice and herbs identification through the ML model. The research undertaken by Naman *et al.* (2023) on the CNN-based ML model for identifying cardamom and the



3(a)



3(b)

Fig. 3: (a) Confusion matrix (b) Training accuracy and validation accuracy for the model developed

auto-ML model built by Chen *et al.* (2023) for 315 traditional Chinese medications provide noteworthy advancements in the domain of herb and spice identification via the use of ML techniques.[14,24] Although there have been numerous studies that have examined the recognition of herbs using datasets of leaf images datasets.[40-46] The presented CNN MobileNetV2 model, in this research attained a remarkable accuracy of 98.69%. The methodology's excellent accuracy, together with positive outcomes from other evaluated standard criteria, establishes it as a viable fundamental element for the digitalization of the authentication process for spices. The originality of this study resides in its emphasis on the identification and authenticity of spices, which sets it apart from previous studies that may have concentrated on other characteristics or plants.

This groundbreaking research creates opportunities for additional investigation, namely in the commercialization of *C. annum* with an emphasis on ensuring high quality. The established ML model's resilience and precision may be used as a foundation for creating comparable models for different spices, therefore enhancing the area of spice authentication. The effective use of machine learning in spice identification might have ramifications for quality assurance, guaranteeing that buyers get genuine and adulteration-free spices.

Identification of the Physical Adulteration in *C. annum* Powder

C. annum powder, a commonly used spice in many cuisines worldwide, is vulnerable to being mixed with inferior substances, which may lead to significant health hazards and undermine the overall quality of the product. This research paper also examines several physical methods used to identify adulterated chili powder. The objective is to provide a thorough analysis of the existing spices and its differentiation from its adulterants. The growing demand for the *C. annum* has resulted in a surge of adulteration methods, jeopardizing its purity and safety.[47,48] Physical adulteration refers to the act of adding foreign compounds to *C. annum* powder, which changes its appearance, texture, or overall composition.

Various type of physical adulterants identified in *C. annum* powder are as following:[47]

- Brick powder: Included to augment hue and volume.
- Sawdust or hardwood particles: Utilized for the purpose of augmenting mass.
- Talcum powder: Included to enhance the consistency.
- Starch and other flours: Used to reduce the concentration of spices.

Analytical Techniques for the Identification of the Adulterants

There are several techniques utilized by various industry involved in the business of chili powder for detecting the adulterants of *C. annum* powder. A few of the commonly utilized techniques are explained below.

Microscopy

It is the scientific practice of using microscopes to examine and evaluate the physical properties of materials at a very small scale. Microscopy is used to analyze the particle morphology of the sample in order to identify adulteration in powdered spices. This method enables the detection of extraneous particles that may have been introduced during the adulteration process.[49-51] Crucial elements of microscopic investigation for identifying adulteration in powder encompass:

- *Particle morphology and dimensions*

Microscopic examination facilitates the determination of the form and size of particles contained inside the spice powder. Wood particles often possess a discernible fiber arrangement, but brick powder particles tend to display uneven forms.

- *Adulterant identification*

Analysts can detect the presence of adulterants in chili powder by comparing observed particles with the known attributes of typical adulterants, such as wood, talcum, or brick powder.

Colorimetry

It is used to evaluate the color consistency of the sample in the context of detecting adulteration in chili powder. Brick powder and other adulterants may cause color changes, which makes colorimetry an important method for detecting these discrepancies.[52–54] Crucial elements of colorimetric analysis in the identification of adulteration in chili powder encompass:

- *Color measurement*

Colorimetry is the process of quantifying the color of a material by measuring factors such as hue, saturation, and brightness. For chili powder, any changes from the anticipated hue may suggest the existence of adulterants.

- *Color standards*

The process of comparing the color of a sample with established color standards or reference samples aids in the identification of any deviations. Regulatory entities or industry associations may establish these standards.

- *Instrumentation*

Colorimeters and spectrophotometers are often used devices for colorimetric analysis. These devices detect the amount of light absorbed or reflected by a material at various wavelengths, giving precise color measurements.

- *Measurement of density*

Density measurement entails the determination of the mass of a material divided by its volume. Density measurement is a useful tool in detecting adulteration in chili powder. It allows for the identification of any differences in the overall density of the sample, which might indicate the presence of probable adulterants.[55–59]

Spectroscopy

Spectroscopy techniques, including infrared spectroscopy (IR) and nuclear magnetic resonance (NMR), are sophisticated analytical procedures that provide comprehensive chemical insights into the composition of chili powder. These methods may be used to identify the existence of certain compounds utilized for adulteration. Spectroscopy methods exhibit exceptional sensitivity and are capable of delivering precise information on the molecular makeup of the sample. Consequently, they serve as excellent instruments for detecting even minuscule quantities of adulterants in powdered spices.[60–63]

Simple Techniques for the Identification of Adulterants in Chili Powder

In order to detect the physical adulterants such as brick powder, salt powder or talc, and synthetic pigments, in chili powder, simple quantitative approaches are mentioned below.[64–66]

Flame test

By combining a tiny quantity of *C. annum* powder with strong hydrochloric acid (HCl) to create a paste and then setting it on fire, a brick red flame is produced. This flame color suggests the existence of calcium salts in the brick powder.

Water sediment test

By dissolving *C. annum* powder in a glass of water and letting it to settle, one may see the presence of sediment at the bottom. The gritty texture may confirm the presence of brick powder or sand, but the presence of soapstone can be indicated by a smooth and soapy residue.

Aqueous solubility test

By sprinkling a tiny amount of *C. annum* powder over the surface of water in a glass tumbler, one may see colorful streaks if artificial colors are present. This test especially focuses on coal tar colors, that are soluble in water.

Tea spoon test

By adding a teaspoon of *C. annum* powder to a glass of water and seeing the resulting-colored water, one may determine the existence of artificial colors. The presence of grittiness in the sediment indicates the presence of either brick powder or sand, while a soapy and smooth residue is indicative of soapstone.

These simple and domestic methods provide a pragmatic strategy for consumers to detect prevalent adulterants in *C. annum* powder. The flame test and water sediment test are dependable markers for the presence of brick powder, but the water solubility and teaspoon tests are efficient in detecting fake colors. By using these qualitative tests, customers may adopt proactive steps to guarantee the integrity and excellence of the *C. annum* powder they use in their everyday culinary endeavors.

Quantitative Analytical Techniques

The concentration of capsaicin in *C. annum* peppers is a crucial determinant of their spiciness and culinary applicability. Another research at the author's lab reported a rapid, economical, and consistent technique for isolating oleoresin capsicum from *C. annum* by optimizing the influence of solvent choice, temperature, and extraction duration. In addition, a reliable and verified high-performance liquid chromatography (HPLC) technique for measuring the amount of capsaicin was developed and validated. The research seeks to provide insights into the selection of *C. annum* cultivars with exceptional capsaicin concentration, which is crucial for quantitative culinary and medical purposes. This study used a reflux technique with polar solvents (methanol, ethanol, chloroform, and acetone) at temperatures varying from 30 to 60°C. The findings demonstrated that the most effective circumstances for extracting capsaicinoids are using acetone as the solvent, with an extraction time of 5 hours and a temperature range of 30 to 60°C. This highlights the significant impact of solvent polarity and extraction conditions on the efficacy of the process.[68]

HPLC method

A quantitative HPLC technique was developed at the author's lab to measure the amount of capsaicin at a wavelength maximum of 280 nm. The approach has been validated and demonstrated a linear response (R^2 = 0.9974) within the concentration range of 1 to 9 µg/mL. The robustness investigations validate the method's dependability under several situations, such as changes in the mobile phase composition, flow rate, and temperature. The developed technique that has been developed effectively measures the amount of capsaicin, with a limit of detection (LoD) of 1.04 µg/mL and a limit of quantification (LoQ) of 3.03 µg/mL. The findings of the accuracy, precision, and robustness investigations adhered to the principles outlined in ICH Q2(R1). The method's capacity to detect capsaicin under diverse circumstances significantly boosts its suitability for regular analysis.

Our study provides a novel approach to extract and measure capsaicinoids exceeding prior methodologies. The extraction procedure used the reflux technique using polar solvents (methanol, ethanol, chloroform, and acetone) for a duration of 5 hours at temperatures varying from 30 to 60°C. Acetone, selected for its polarity, exhibited the greatest production of capsaicinoids, highlighting the effectiveness of the approach. Compared to other procedures such as percolation, maceration, and sonication, the reflux method is notable for its safety, simplicity, and decreased solvent needs.[68–71]

Our developed method offers a complete and efficient solution for extracting capsaicinoids. It combines practicality, safety, and efficacy, representing substantial progress in the study of oleoresin capsicum. Moreover, it opens up possibilities for future applications and research in this area.[67,72-74]

Discussion

Integrating machine learning (ML) models with conventional qualitative and quantitative approaches shows great potential in the field of spice adulteration detection. This approach offers a viable way to guarantee the authenticity and safety of spices. The research article aims to tackle the widespread problem of spice adulteration, specifically in relation to *C. annum* as a representative study. It suggests a comprehensive strategy that combines ML models, for differentiation based on distinct features, qualitative (physical) and quantitative method (HPLC) to check adulteration and detect its quality. This approach is designed to guarantee the genuineness and safety of spices. The paper underscores the harmful consequences of adulteration on both public health and culinary traditions, while emphasizing the monetary incentives that drive these deceitful tactics. In order to combat spice adulteration, it is suggested to use ML models and artificial intelligence. These technologies have the ability to scan extensive datasets and identify intricate patterns in the composition of spices. The authors examine the difficulties linked to conventional authentication methods and chemical studies, emphasizing the need for more sophisticated and effective procedures.

An important feature emphasized in the study is the use of transfer learning techniques, specifically making use of pre-trained models such as MobileNetV2. Transfer learning enables the adjustment of pre-trained models, which were originally trained on extensive datasets, to the particular goal of identifying spices. The study presents a methodical approach for constructing ML models to identify spices, encompassing several processes, *viz*. data collection, pre-processing, model selection, transfer learning, customization, training, hyperparameter tweaking, and assessment. The authors highlight the significance of using transfer learning methodologies, capitalizing on pre-trained models such as MobileNetV2, to improve both efficiency and accuracy. The paper presents a case study that describes the creation of a CNN-MobileNetV2 model specifically designed for chili identification. The research subsequently broadens its focus to include the detection of other spices and herbs, with the objective of developing a more comprehensive and flexible ML model to address the wider task of distinguishing other spices and identifying their adulterants. This process reduces the computational workload and improves efficiency without sacrificing accuracy. This strategy is especially advantageous in situations when obtaining a sufficiently extensive dataset for training from the beginning may be difficult or not feasible.

Moreover, the research examines the process of identifying physical adulteration in chili powder, specifically investigating industrial methods such as microscopy, colorimetry, density measurement, and spectroscopy.

Furthermore, the study highlights the significance of quantitative analytical techniques, such as HPLC, alongside ML-based approaches. These methods are crucial for accurately measuring important components, such as capsaicin, in different types of chili. The careful adjustment of HPLC parameters, such as solvent choice, temperature, and extraction time, highlights the importance of accurate analytical methods in evaluating the quality and pungency of spices.

Additionally, it presents simple and domestic techniques for customers to identify prevalent contaminants like brick powder and synthetic dyes in chili powder, offering a pragmatic approach to guarantee the excellence of the seasoning used in daily culinary preparations. HPLC method for quantification of capsaicin concentration in *C. annum* varieties, for its selection on evaluating their level of spiciness. The authors have devised an HPLC method to detect capsaicin and highlight the significance of selecting the appropriate solvent, temperature, and extraction period to get the best possible outcomes.

In conclusion, the study recognizes the importance of the advancement of ML models for spice authentication and the creation of effective techniques for consumers to detect adulterants. These technologies emphasize the potential influence they may have in protecting public health and conserving culinary traditions. Nevertheless, study acknowledges the presence of research deficiencies for a comprehensive approach by integrating ML models its practical applications by all stakeholders along with the physical and chemical quality check methodologies. Hence the study emphasizes on further application of integrative multidisciplinary approaches for the other spices and herbal drugs to extrapolate these finding at large scale.

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