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Digital image-based detection of wheat flour adulteration in turmeric powder: A deep learning approach

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Abstract
Assessing the quality of food and spices is crucial for ensuring human nutrition. Researchers have explored non-destructive methods, particularly computer vision, for measuring food and spice quality. This study emphasizes the significance of quality assessment for turmeric, given its high nutritional value and susceptibility to fraudulent practices. Low-quality wheat powder, due to its low market price, becomes an attractive option for adulterating turmeric powder. The research employs an improved convolutional neural network (CNN) to classify turmeric powder images and detect fraud. A dataset of 3000 image samples is categorized into six groups, encompassing pure turmeric powder and various levels of adulteration with wheat flour (10%, 15%, 20%, 25%, and 34%). The study aims to enhance fraud detection capabilities, contributing to the preservation of turmeric's integrity in the market. During the initial image processing step, undesired components were eliminated. Employing data augmentation (DA) was crucial to mitigate overfitting issues in the convolutional neural network (CNN). Specifically, the VGG-16 (Visual Geometry Group 16 layer) model architecture was deployed for the classification task. In implementing this deep learning approach, the image dataset was randomly partitioned into two primary sets: 90% for the training-validation phase of the CNN and 10% designated for a blind test. The refined model exhibited an impressive 92.7% accuracy during the validation phase, with a minimal 5.6% misclassification rate observed in blind testing. This underscores the efficacy of the method as a quality and safety control measure for the turmeric industry. The study outcomes also underscore the potential of computer vision, particularly in conjunction with deep learning (DL), as a valuable tool for assessing quality and uncovering fraudulent practices in turmeric powder.

Keywords: Digital, wheat, flour, learning, turmeric, powder

1. Introduction

The issue of food scarcity is multifaceted and significant, arising from the burgeoning global population, recent upswings in the prices of agricultural products and spices, the appreciating value of the dollar, and economic deceleration in numerous Western nations. In addition to the challenges posed by food shortages and escalating prices, complications arise from factors such as food fraud. Exploitative individuals and fraudsters engage in food fraud to maximize profits, posing risks to public health. Considering the pivotal role of food in daily life and the inadequacy of current food fraud detection measures due to the exorbitant costs of tools, equipment, and time-intensive analytical methods, there is an urgent need to devise simple, swift, and cost-effective techniques for ascertaining food quality. A novel approach in assessing food quality involves the utilization of image processing techniques. While commercial implementations of these technologies have been available for less than a decade, they have garnered significant esteem within the scientific communities of Iran and globally for their efficacy in monitoring the quality of agricultural products and food items. The practical demand for rapid, precise, and automated determination of food attributes is evident in daily life. Various modern technologies, encompassing computer vision, electronic noses, spectroscopy, spectral imaging, and more, have gained widespread application in detecting food attributes, generating copious amounts of digital information related to food properties. Effectively managing such extensive datasets and extracting relevant features are critical tasks due to the abundance of redundant and irrelevant information.

Addressing this challenge is both urgent and pivotal, as it directly influences the real-world application of these techniques. Numerous data analysis methods, including Partial Least Squares Regression (PLSR), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Particle Swarm Optimization (PSO), Fuzzy logic, and Euclidean Distance Transform (EDT), have been developed to tackle extensive datasets in modeling. Deep Learning (DL), an influential machine learning algorithm, has gained widespread attention across diverse fields such as remote sensing, agriculture, medicine, robotics, healthcare, human action recognition, and speech recognition. DL excels in autonomously learning data representations, even for multidomain feature extraction, transfer learning, coping with vast datasets, and achieving superior performance and precision. Convolutional Neural Networks (CNN) and their derivatives are recognized as pivotal methods in various studies. They automatically acquire deep features from input digital information for subsequent classification or regression tasks. DL, particularly CNN, proves adept at processing the substantial datasets obtained through tools used in food quality and safety evaluation. Spices hold significant value in the food and pharmaceutical industries, making the identification and classification of spices based on purity crucial. Fraudulent practices by profiteers involve preparing spice mixtures with a cheaper component masquerading as a more expensive one, solely for economic gain. This deceptive food and spice fraud pose risks to the general health of society, emphasizing the importance of robust methods, such as DL, in detecting and preventing such fraudulent activities.

Turmeric, renowned since ancient times for its antimicrobial properties, has been a staple spice globally and a cornerstone in traditional medicine, particularly in Ayurveda. The significance of turmeric lies in its component, curcumin, known for proven bioactivities such as antioxidation, anti-inflammation, antiseptic qualities, analgesic properties, and anticarcinogenic effects. This has fueled an escalating international demand for turmeric in recent years. However, the widespread popularity of turmeric powder has attracted unscrupulous profiteers seeking to adulterate it for extra gains. Common adulterants include wheat flour, rice flour, starch, and chalk dust, often colored with various dyes and colorants such as metanil yellow, lead chromate, and tartrazine. To combat this fraudulent activity, researchers have turned to advanced technologies like computer vision and deep learning. Liu *et al*., (2020) [8] in their study, utilized computer vision and deep learning to detect fraud in chrysanthemum tea, achieving high prediction accuracies of 90% for classifying flowering stages and 63% for tea types. Rashvand *et al*., (2018) [20] developed an olive oil fraud detection system employing image processing and dielectric spectroscopy. Their results demonstrated the effectiveness of neural networks in predicting mixed samples of olives and sunflower seeds, as well as olives and rapeseed, with high correlation coefficients and minimal mean square errors. In a similar vein, Mohamadzadeh-Moghadam *et al*., (2020) [11]. employed a machine learning technique and SVM linear classifier to classify saffron based on color characteristics. These technological advancements showcase the potential of cutting-edge methods in preserving the integrity of valuable and sought-after commodities like turmeric in the face of fraudulent practices. Their research yielded an average accuracy of 82.23% using the SVM linear classifier. Turmeric, valued for its nutritional and therapeutic properties, is commonly available in powder form in the market, making it susceptible to fraudulent activities. Conventional sensory evaluation methods for assessing spice quality face limited adoption due to their time-consuming nature, high costs, and propensity for errors. Both industry stakeholders and researchers are keen on preserving the quality of food and pharmaceutical products through non-destructive technologies. In light of these considerations, this study endeavors to assess the visual system's efficacy as a non-destructive technology for distinguishing authentic turmeric from counterfeit variants in the consumer market.

2. Materials and Methods

2.1 Sample collection

In this study, 25 pure turmeric samples, comprising 5 certified and reputable brands (5 powder packets from each brand), were acquired to conduct the experiment. The initial step involved preparing the turmeric rhizome, which was subsequently pulverized using a grinder. Given the diverse range of materials and substances available for adulterating foodstuffs and spices, the economical and readily available nature of low-grade wheat flour made it a suitable choice for blending with turmeric in powder form and subsequently selling in the market (Fig. 1). Therefore, aligning with the study's objectives, wheat powder was selected as a representative example of fraudulent adulteration in turmeric powder.

2.2 Preparation of the samples

In Preparation of the samples, turmeric was mixed uniformly with wheat powder at 5 concentration level from 10% to 30% at 5% interval. Each sample of 25 pure sample adulterated with wheat powder at 5 concentration level from 10% to 30% at 5% interval, so total number of samples for image acquisition were 150 (25 pure and 125 adulterated).

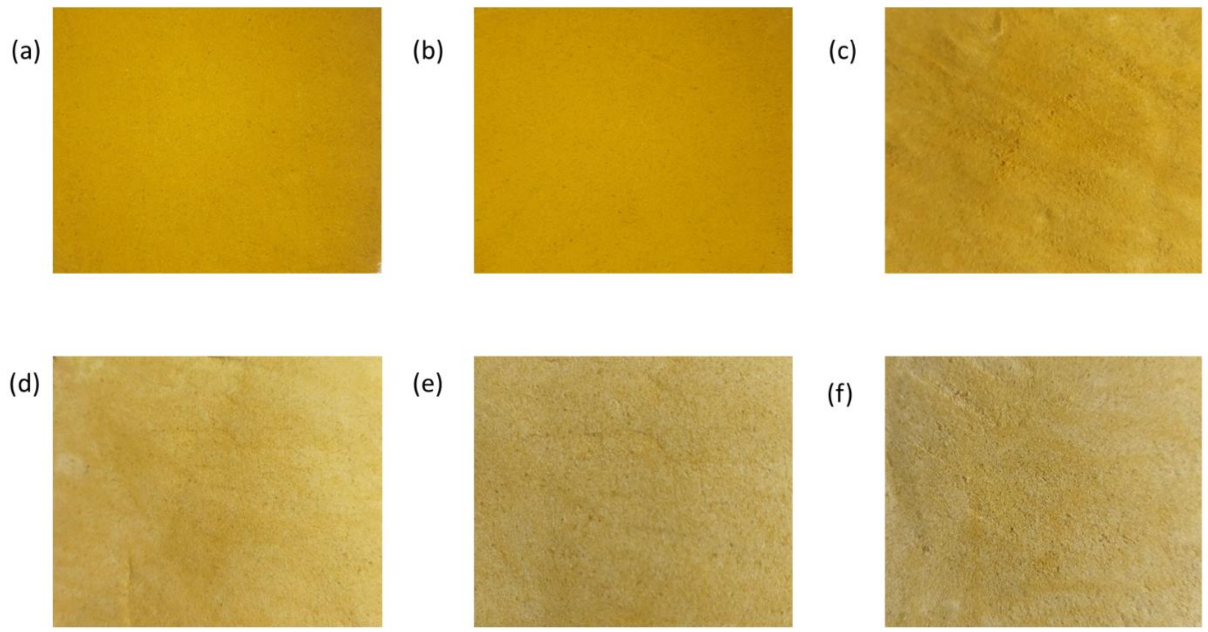

Fig 1: (a) Pure turmeric powder, (b) 10% adulterated with wheat powder, (c) 15% adulterated with wheat powder, (d) 20% adulterated with wheat powder, (e) 25% adulterated with wheat powder, and (f) 30% adulterated with wheat powder

2.3 Digital image acquisition system

For standardized digital images in this study, a light box was crafted from 0.5 cm thick wood, featuring dimensions of 40 × 40 × 20 cm, and a hinged front panel for convenient sample replacement. Positioned in the upper center of the light box was a Nikon Z30-16_50MM digital camera with a 20-megapixel resolution. The camera lens was mounted inside the box, maintaining a 15 cm distance from the sample. To ensure even lighting, the lens was directed through a circular fluorescent light source. RGB digital images were manually captured and saved in JPG format. In Fig. 1, images illustrating turmeric adulterated with wheat powder classes are presented, providing a visual representation of various adulteration levels within the dataset. Throughout the image acquisition process, the camera settings remained consistent. To produce the images, the position of the paper was adjusted and repositioned five times for each individual sample. This meticulous repetition resulted in a total of five images for each sample, ensuring comprehensive coverage of the dataset. Consequently, in total, 750 images were acquired for six class of adulteration, with each class contributing 25 images (calculated as 1 adulteration level = 5 captures × 5(number of samples of each brand) × 5 brands = 125 images, total image = 5 brands × 5 (number of samples of each brand) × 6 classes × 5 captures = 750 images). This methodological approach enabled the comprehensive collection of visual data essential for subsequent analysis and interpretation.

Total number of Images taken by camera for each class = 5 (Number of brand) × 5(number of samples of each brand) ×4 (number of capture) = 125

Table 1: Experiment design for image acquisition

Sr. No	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
	Brand/pure turmeric	Adulteration level 1	Adulteration level 2	Adulteration level 3	Adulteration level 4	Adulteration level 5
1.	Brand 1	10% conc.	15% conc.	20% conc.	25% conc.	30% conc.
2.	Brand 2	10% conc.	15% conc.	20% conc.	25% conc.	30% conc.
3.	Brand 3	10% conc.	15% conc.	20% conc.	25% conc.	30% conc.
4.	Brand 4	10% conc.	15% conc.	20% conc.	25% conc.	30% conc.
5.	Brand 5	10% conc.	15% conc.	20% conc.	25% conc.	30% conc.

2.4 Proposed method

In the laboratory environment, a dataset comprising 6 distinct classes of turmeric and turmeric mixtures was meticulously created. The images of these blends underwent preprocessing using RGB color spaces and were subsequently classified through transfer learning algorithms. The model developed in this study represents a comprehensive solution to the pervasive issue of food adulteration, employing RGB color spaces and artificial intelligence architectures. The preprocessing of images involved several techniques, including selecting a square region of interest, splitting, cropping, and converting them into RGB arrays. Each set of processed images was then subjected to classification using various deep learning algorithms. The performance of the model was rigorously analyzed through the utilization of a confusion matrix. By scrutinizing the classification results, the study aims to effectively address the problem of food adulteration and aims to provide valuable insights for future research in this critical field.

2.5 Images pre-processing and data preparation

The sample images of turmeric from six classes (one pure and five adulterated at 10% intervals from 10% to 30%) were initially captured on a white paper. To isolate the powder images and remove the background, a square-shaped portion was selected from each image, resulting in an image size of 6720 × 4480 pixels. Recognizing that working with such large image sizes could increase parameters for Convolutional

Neural Network (CNN) training and slow down image processing, the researchers devised a solution. To optimize the process without compromising quality, each image was divided into four equal, non-overlapping parts. This division resulted in 500 images per class (125 × 4 = 500). Beyond computational efficiency, this approach served to enhance the dataset and prevent overfitting in the CNN model. Subsequently, feature extraction was performed on the original 3000 images from the six classes of turmeric used in the study. Feature extraction involves obtaining relevant features from the input image dataset. In this study, RGB color features were extracted using image processing techniques. These features play a pivotal role in classifying different classes of turmeric powder, contributing to the effectiveness and accuracy of the CNN model in distinguishing between pure and adulterated turmeric samples.

2.6 Data augmentation (DA)

Data augmentation (DA) is a well-established technique frequently employed in the realm of Convolutional Neural Networks (CNNs) to address the network's requirement for extensive annotated data for effective object classification. This technique aims to expand the dataset, thereby improving the accuracy of the CNN network. By introducing more varied training data, the learning process is enhanced, and the risk of network overfitting is mitigated. Essentially, data augmentation is a method used in deep networks to supplement existing datasets by generating new training images from the current samples. This augmentation involves applying diverse transformations, including random adjustments to brightness and contrast, random flipping and rotation, and random jitter, among others, to the original images. These transformations ensure that the new images retain the characteristics of the originals and are visually classified into the same category. The augmented dataset improves the CNN's ability to generalize and learn robust features, ultimately leading to enhanced performance in object classification tasks. This results in improved performance on new and unseen data, as the model learns to handle diverse variations and avoids overfitting to specific instances. In this study, DA using image rotation was performed at a 45° angle in 7 steps (up to 315°), and DA images were obtained during the process of image flipping in 3 steps. A total of 10 augmented images were generated from a single original image, with 7 resulting from image rotation and 3 from image flipping. The image dataset for each class contained 500 original images, bringing the total number of samples in the six classes to 3000 original images.

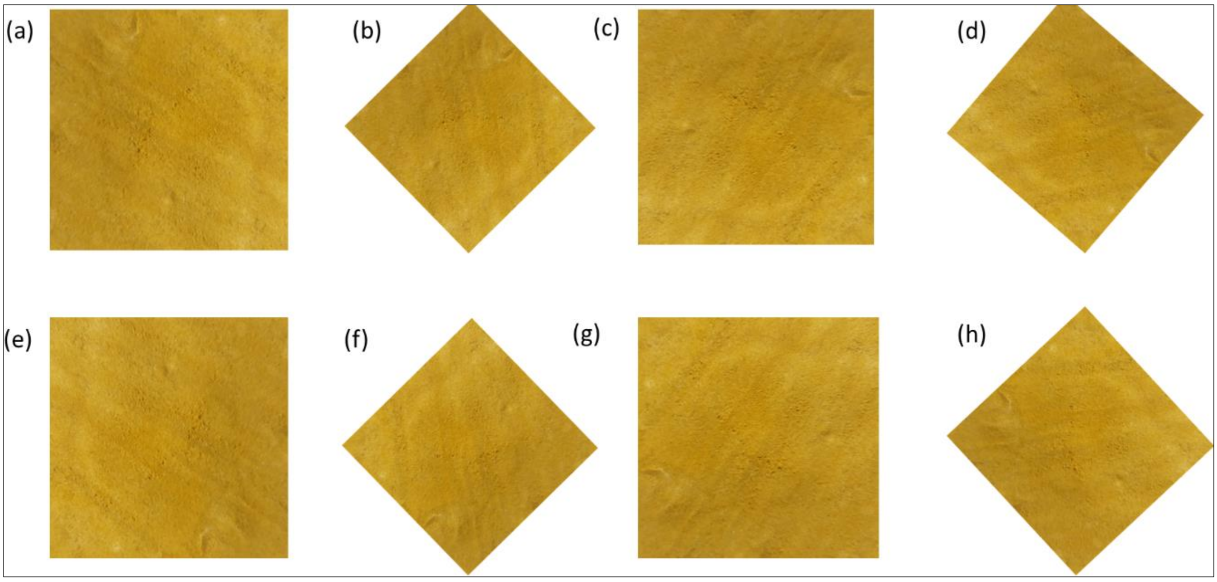

Fig 2: DA using image rotation: (a) Original image, (b) 45° rotation, (c) 90° rotation, (d) 135° rotation, € 180° rotation, (f) 225° rotation, (g) 270° rotation, and (h) 315° rotation

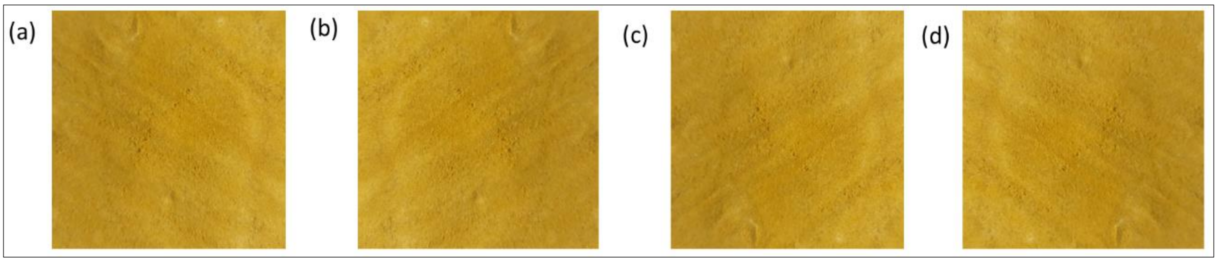

Fig 3: DA by image flipping: (a) Original image, (b) Flip horizontal, (c) Flip vertical, and (d) Flip horizontal and vertical

2.7 The architecture of the CNN

In the realm of pattern recognition and image classification, supervised Convolutional Neural Networks (CNNs) stand out as one of the most potent mathematical algorithms (Islam *et al*., 2018) [21]. Their prowess can be attributed in part to the initial steps, where the focus lies on selecting the most distinctive features of the images for classification. This pivotal task is carried out within the convolutional and pooling layers (Rusk, 2015) [16]. Following this feature extraction process, the subsequent stage involves classification using the initially selected features (Ting *et al*., 2019) [18]. This classification task is executed through conventional supervised neural networks, commonly referred to as multilayer perceptron (MLPs), which constitute the fully connected layers of the CNNs. The intricate interplay of these two steps forms the foundation of the CNN's ability to effectively recognize and classify patterns in images.

2.8 Convolutional and pooling layers: To identify the prominent distinguishing features of images, Convolutional Neural Networks (CNNs) incorporate digital filters based on fixed-dimensional matrices directly applied to input images. These filters, having lower dimensions than the input image, necessitate the definition of a parameter indicating the filter's offset within the image, known as "stride." The typical value for this parameter is one, and it has been utilized in this study (Ng *et al*., 2019) [14]. The application of these filters, along with the selection of differentiating features, results in the reduction of the input image dimension by increasing the number of matrices per photograph (Ting *et al*., 2019) [18]. This augmentation of matrices per image is achieved through algorithms that choose either average or maximum values from sub-matrices. In this study, the "max-pooling" algorithm selects the maximum values from the generated sub-matrices. Subsequently, an activation function is applied to normalize the obtained values. In this work, the Rectified Linear Unit (ReLU) function is employed ($f(x) = \max(0, x)$) (Morandi *et al*., 2012) [12]. The ReLU function introduces non-linearity to the model, aiding in learning complex patterns and enhancing the overall performance of the CNN.

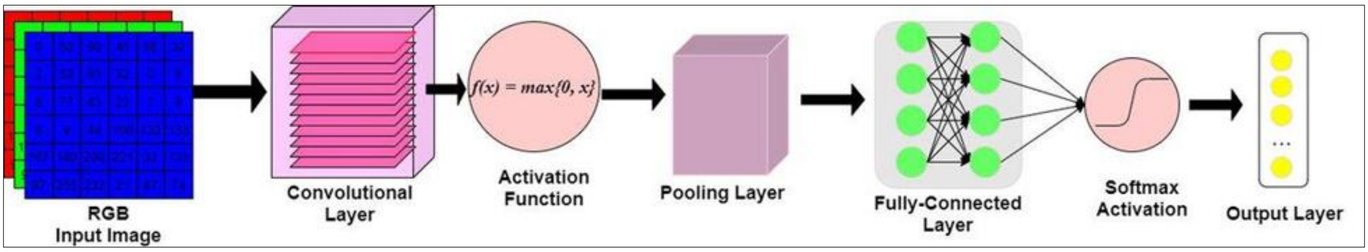

Fig 4: Common architecture of CNN (https://www.learndatasci.com/tutorials/hands-on-transfer-learning-keras/)

Fully connected layers, often represented by Multilayer Perceptron (MLPs), utilize the information provided by the convolutional and pooling layers to determine the class to which a given image belongs. The number of output variables in these layers, and consequently in the CNN model, corresponds to the number of classes into which the photographs are classified. The optimization process of the CNN involves entropic algorithms and a regularization method (Seki *et al*., 2017; Ting *et al*., 2019; Izquierdo *et al*., 2020) [17, 18, 5]. Given the iterative nature of the learning phase in these algorithms, the step size of each iteration within the parameter optimization process is defined, controlled by the learning coefficient (Torrecilla *et al*., 2008) [19]. Determining the optimal value for the learning coefficient is critical to optimizing all CNN parameters and enhancing the overall generalization ability of the CNN (Yamashita *et al*., 2018). to classify turmeric powders into their respective groups, the Softmax function is applied as the activation function mainly in the fully connected layers. The Softmax function calculates the probability of each image belonging to a specific class. To streamline the optimization process and the use of the developed model, mini-batches of randomly selected images are employed. These mini-batches facilitate the optimization process of the CNN model (Lawrence *et al*., 1997) [9]. In this study, a VGG-16 (Visual Geometry Group 16 layer) model architecture was implemented due to its strong performance in various applications requiring image classification. The VGG-16 neural network, renowned for its deep convolutional architecture, is employed in the innovative task of identifying wheat flour adulteration in turmeric powder. Leveraging its 16 layers of trainable parameters, VGG-16 proves to be a potent tool for image classification tasks. In this context, the neural network is trained on a diverse dataset encompassing authentic turmeric powder images and samples tainted with varying concentrations of wheat flour. The network learns intricate features and patterns that distinguish pure turmeric from adulterated counterparts. Through its hierarchical structure of convolutional layers, VGG-16 adeptly captures the nuances in color, texture, and composition, facilitating accurate discrimination. This application of VGG-16 not only ensures the detection of adulteration but also underscores the versatility of deep learning in addressing complex real-world challenges, offering a robust solution for quality assurance in food products.

The dataset of 3000 images underwent random division into three groups to execute distinct tasks within the optimization process. Specifically, 90% of the images were allocated for the initial training and validation of the model, while the remaining 10% were reserved for a simulated blind test to evaluate the model's performance with samples not previously processed (Torreblanca-Zanca *et al*., 2019) [22]. The statistical performance of the algorithms will be quantified by calculating the percentage of correct classification for each class during both the validation and blind testing processes. This evaluation metric provides insights into the model's accuracy in correctly categorizing images across different classes, offering a comprehensive assessment of its effectiveness.

2.9 Parameter setup for training of CNN

The model was trained in MATLAB 2020, and the experiments were conducted entirely within a in window 10 core i5 environment. MATLAB served as the primary programming language for both the development and training of the model. The decision to use MATLAB was driven by its powerful numerical computing capabilities and extensive toolboxes tailored for machine learning tasks. 90% of the images were allocated for the initial training and validation of the model, while the remaining 10% were reserved for a simulated blind test to evaluate the model's performance with samples not previously processed. The images were rescaled to 224 × 224 pixels when provided as input to the CNN network. The batch size for training the CNN network was set at 64 for each group. The training process comprised 50 epochs, and the learning rate was fixed at 0.0001. These parameters were carefully chosen to optimize the training process and achieve the desired performance in image classification.

Table 2: Optimized parameters for VGG-16 model trained to classify pure and adulterated turmeric powder samples.

Parameters	Values
Learning rate	0.0001
Size of inputted images (vertical pixels ×horizontal pixels ×RGB channels)	224×224×3
Stride	1
Number of epochs	6
Mini-batch size	64
Optimizer	Stochastic Gradient Descent (SGD)
Loss Function	Categorical cross entropy
Data Augmentation	Rotation and mirroring

2.10 Performance metrics

The present study involved evaluating various deep learning models within each color space, utilizing performance metrics accuracy rates. its values were computed using confusion matrices, which involved calculating performance measurements, including TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative). The metrics were computed using the equations (1).

- True Positive (TP) refers to the accurate identification of positive values in the real class.
- False Negative (FN) describes the incorrect estimation of positive values in the real class.
- False Positive (FP) represents the number of predictions where the classifier mistakenly forecasts the negative class as positive.
- True Negative (TN) in the confusion matrix denotes the correct classification of negative instances of the actual class.

By leveraging these parameters, the study effectively assessed the performance of the deep learning models across different color spaces. This approach provided valuable insights into their classification capabilities for the specific task under consideration.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100 \qquad (1)$$

3. Results and Discussion

3.1 Image conditioning

To ensure the accurate classification of the six classes of turmeric powders, including both pure and adulterated samples, a total of 125 images were captured for each class. These images were acquired using the JPEG file format and possessed pixel dimensions of 6720 × 4480 pixels. The visual representation of the six classes of turmeric powder is presented in Fig. 1. this illustration emphasizes that distinguishing between these various classes of turmeric powder solely through visual inspection is not feasible within this specific context. Consequently, the adoption of mathematical techniques becomes imperative. Convolutional Neural Networks (CNNs) emerge as a crucial mathematical approach in this scenario. These networks serve as essential tools for effectively classifying discrete sets of image data. Given the inherent challenge of visually differentiating among the six classes of turmeric powder, CNNs play a crucial role in achieving accurate classification. The tool developed through this process facilitates the precise categorization of the six distinct classes of turmeric powder, providing researchers and practitioners with a reliable means to confidently discern between these variations.

3.2 Optimization, verification, and blind testing of the CNN

For the detection and classification of pure samples, as well as wheat flour adulterated turmeric powder, a single CNN was used. For this purpose, the total images have been randomly divided into two initial groups, one for training and verification, containing approximately 80% of the images (2400), and a second for blind testing (20% of images: 600). It should be noted that three were total 3000 photographs in the database. An initial rough classification of the images employed for training and validation was performed, where 80% were used as training set (1920) and 20% for validation purposes (480). Afterwards, the images separated as blind samples are fed to the optimized model to validate its performance with images never seen before by the CNN.

3.2.1 Training and verification of the VGG-16 CNN powdered turmeric classifier

The network architecture used is based on the VGG-16 CNN model. This algorithm is a pre-trained network, with fixed weight values, which is adapted to the current task via transfer learning. This CNN model is designed for the classification of images of pure and wheat flour-adulterated turmeric powder with one of 5 different concentrations. Following the transfer learning-based procedure, in order for it to detect the patterns needed for the classification of the turmeric images, the weights contained in the last layers of the network need to be modified or reoptimized. It must be noted that the images have been cropped to a square photograph of 224 pixels thus greatly reducing the computational requirements of the CNN algorithm. The main parameters used in the network are listed in Table. 2 After training the CNN, internal validation was performed by means of the verification dataset. The resulting confusion matrix is shown in the fig. 5. Of the 480 images, the model misclassified 35 images of validation dataset, leading to a misclassification rate of 7%. Confusion matrix shows the individual classification errors. As can be seen in Confusion matrix, all sample of pure turmeric (class 1), 10% wheat flour adulteration (class 2), and 15% wheat flour adulteration (class 3) were classified correctly with 100% accuracy. 8 sample of class 4 misclassified, and 13 Sample of class 5 misclassified, 14 sample of class 6 were misclassified. These facts combined with a nearly 92.7% accuracy suggest the high degree of reliability and robustness of the model.

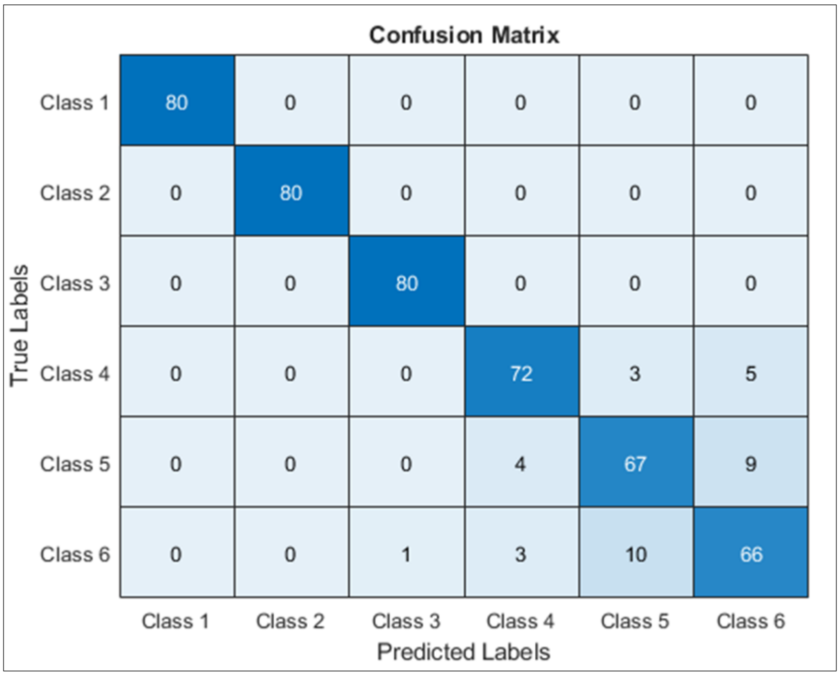

Fig 5: Confusion Matrix for Validation dataset

3.2.2 Testing with blinded images

Of the 600 images that were randomly separated from the database to be used as blind testing, 34 sample images of blind testing dataset were misclassified, resulting in a 94.33% accuracy. The images that were misclassified, as well as their predicted classifications are shown in confusion matrix in fig. 6. Besides the strong statistical performance, it can be seen that only one image of pure turmeric has been classified as adulterated. Of the 600 images, the model misclassified 34 images of blind test dataset, leading to a misclassification rate of 5%. confusion matrix shows the individual classification errors. As can be seen in confusion matrix, all sample of pure turmeric (class 1), 10% wheat flour adulteration (class 2), and 15% wheat flour adulteration (class 3) were classified correctly with 100% accuracy as was in blind test data set. 13 sample of class 4 misclassified, and 14 sample of class 5 misclassified, 7 sample of class 6 were misclassified. These facts combined with a nearly 94.33% accuracy suggest the high degree of reliability and robustness of the model. In comparison with other detection techniques, the presented approach has significant advantages. Namely, the turmeric evaluation time (real-time analysis is possible), the reduced costs, the greater portability of the equipment, and the fact that the need for sample preparation is non-existent. On the other hand, it should be noted that analyses performed in laboratories, with powerful equipment, reveals accuracies closer to 100%, although the detection limits still hover around those presented in this work.

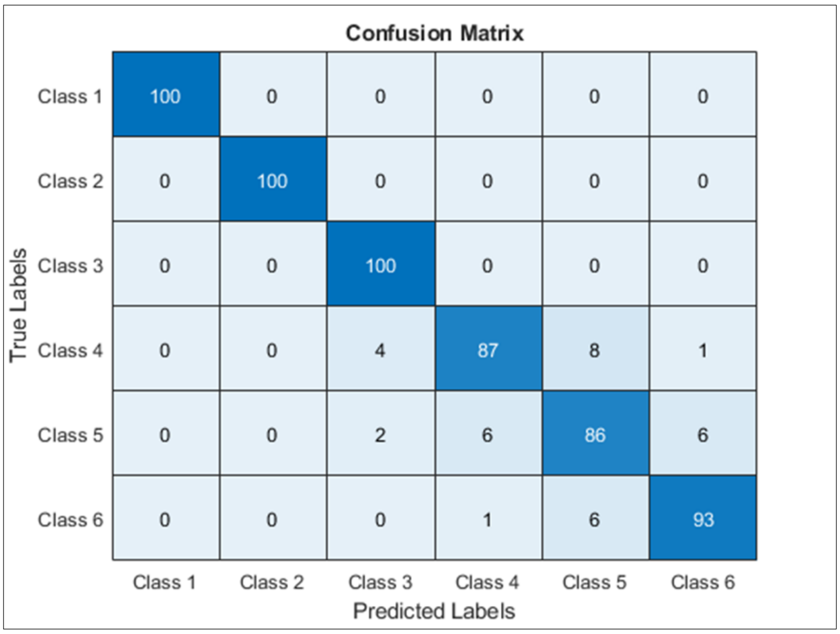

Fig 6: Confusion matrix for blind testing dataset

4. Conclusions
In this work, a tool based on deep learning has been presented to quantify wheat flour adulteration turmeric powder samples based on RGB color value difference of pure and adulterated turmeric powder. Simply employing common photographs of the turmeric samples, the classification of six types of powdered turmeric and their corresponding adulterations with wheat flour different at concentrations (Pure, 10%, 15%, 20%, 25%, and 30%). A total of 600 images were captured and converted into 3000 original image using image processing for the development of Convolutional Neural Networks (CNNs), with each group designated for classification consisting of 500 images. Specifically, the classification was conducted using the VGG-16 model architecture. In this deep learning approach, the images were randomly partitioned into two primary sets: 90% for the training-validation phase of the CNN and 10% allocated for a blind test. The optimized model demonstrated an impressive overall accuracy of 92.7% during the validation phase. Moreover, when subjected to blind testing, the model exhibited a misclassification rate of 5.6%, underscoring its efficacy as a method for quality and safety control in the turmeric industry. This outcome highlights the robustness and reliability of the developed model in ensuring the integrity and safety of turmeric powder.

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