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Turmeric integrity unveiled: A deep learning approach for detecting rice flour adulteration in turmeric powder

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Abstract
Evaluating the quality of food and spices is essential to ensure human nutrition. Non-destructive methods, such as computer vision, have been explored by researchers for assessing the quality of food and spices. This research specifically highlights the importance of quality assessment for turmeric, given its nutritional value and vulnerability to fraudulent activities. The affordability of low-quality rice powder makes it an enticing option for adulterating turmeric powder due to its lower market price. To address this issue, the study utilizes an enhanced convolutional neural network (CNN) for classifying turmeric powder images and detecting fraud. A dataset comprising 3000 image samples is divided into six categories, representing pure turmeric powder and varying levels of adulteration with rice flour (10%, 15%, 20%, 25%, and 34%). The primary objective is to improve fraud detection capabilities, thereby safeguarding the integrity of turmeric in the market. In the initial image processing stage, unwanted components are removed. The incorporation of data augmentation (DA) proves crucial to address overfitting concerns in the CNN. Specifically, the MobileNet-v2 model architecture is employed for the classification task. In implementing this deep learning approach, the image dataset is randomly divided into two main sets: 90% for training-validation in the CNN and 10% designated for a blind test. The refined model demonstrates an impressive 90% accuracy during the validation phase, with a minimal 7% misclassification rate observed in blind testing. This highlights the effectiveness of the method as a quality and safety control measure for the turmeric industry. The study's findings underscore the potential of computer vision, especially in combination with deep learning (DL), as a valuable tool for assessing quality and exposing fraudulent practices in turmeric powder.

Keywords: Turmeric integrity, approach turmeric, powder, adulteration

Introduction

The challenge of food scarcity is complex and substantial, stemming from factors such as the expanding global population, recent spikes in agricultural and spice prices, the strengthening value of the dollar, and economic slowdowns in numerous Western nations. Alongside the issues of food shortages and rising prices, complications arise from phenomena like food fraud, where exploitative individuals and fraudsters engage in deceptive practices to maximize profits, thereby posing risks to public health. Given the central role of food in daily life and the limitations of existing food fraud detection methods due to their high costs in terms of tools, equipment, and time-intensive analytical processes, there is an urgent need to develop straightforward, rapid, and cost-effective techniques for ensuring food quality. A novel approach to assessing food quality involves the application of image processing techniques. Despite being commercially available for less than a decade, these technologies have gained significant recognition within the scientific communities of Iran and globally for their effectiveness in monitoring the quality of agricultural products and food items. The practical demand for swift, precise, and automated determination of food attributes is evident in everyday life. Various modern technologies, including computer vision, electronic noses, spectroscopy, spectral imaging, and more, have found widespread application in detecting food attributes, generating large amounts of digital information related to food properties. Effectively managing extensive datasets and extracting pertinent features are critical tasks due to the abundance of redundant and irrelevant information. Addressing this challenge is both urgent and pivotal, as it directly impacts the real-world application of these techniques. Several data analysis methods, such as 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 handle extensive datasets in modeling. Deep Learning (DL), a powerful machine learning algorithm, has garnered widespread attention across diverse fields, including 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, automatically acquiring deep features from input digital information for subsequent classification or regression tasks. DL, especially CNN, proves adept at processing substantial datasets obtained through tools used in food quality and safety evaluation. Spices, with significant value in the food and pharmaceutical industries, necessitate the identification and classification based on purity. Fraudulent practices involve profiteers 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, underscoring the importance of robust methods like DL in detecting and preventing such fraudulent activities.

Turmeric, renowned for its antimicrobial properties since ancient times, has been a globally cherished spice and a cornerstone in traditional medicine, especially in Ayurveda. The significance of turmeric lies in its component, curcumin, which is known for various proven bioactivities such as antioxidation, anti-inflammation, antiseptic qualities, analgesic properties, and anticarcinogenic effects. This has led to a growing 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 like metanil yellow, lead chromate, and tartrazine. To counteract this fraudulent activity, researchers have turned to advanced technologies such as computer vision and deep learning. In a study by Liu *et al*., (2020) [8] computer vision and deep learning were employed to detect fraud in chrysanthemum tea, achieving high prediction accuracies of 90% for classifying flowering stages and 63% for tea types. Another study by Rashvand *et al*., (2018) [20] developed an olive oil fraud detection system using 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. Similarly, Mohamadzadeh-Moghadam *et al*., (2020) [21] utilized a machine learning technique and SVM linear classifier to classify saffron based on color characteristics. These technological advancements underscore the potential of state-of-the-art methods in safeguarding the integrity of valuable commodities like turmeric against fraudulent practices. The research outcomes revealed 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, rendering it susceptible to fraudulent activities. Traditional sensory evaluation methods for assessing spice quality encounter limited adoption due to their time-consuming nature, high costs, and susceptibility to errors. Both industry stakeholders and researchers are eager to preserve the quality of food and pharmaceutical products through non-destructive technologies. In consideration of these factors, this study aims to evaluate the effectiveness of the visual system as a non-destructive technology for distinguishing authentic turmeric from counterfeit variants in the consumer market.

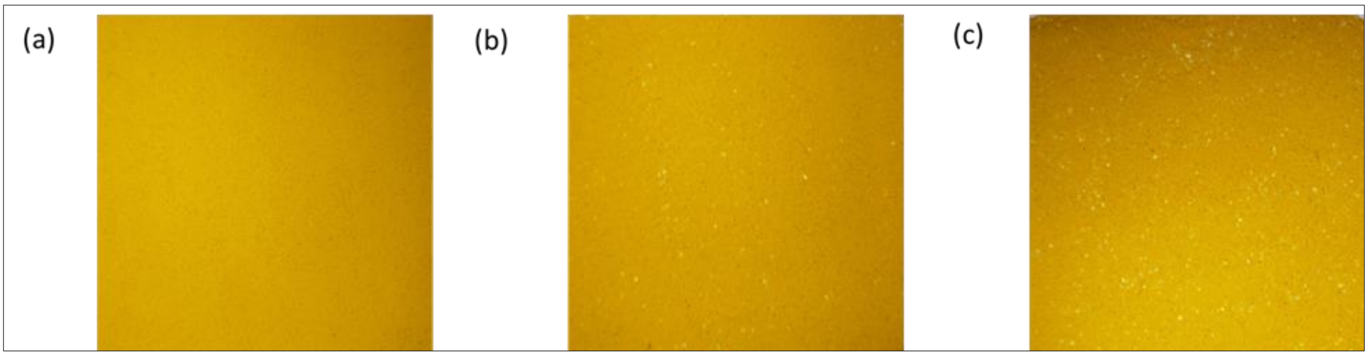
2. Materials and Methods

2.1 Sample collection

For this study, 25 pure turmeric samples were obtained, comprising 5 packets from each of 5 certified and reputable brands. The experiment commenced with the initial step of preparing the turmeric rhizome, which was subsequently pulverized using a grinder. Recognizing the diverse array of materials and substances used to adulterate foodstuffs and spices, the cost-effectiveness and ready availability of low-grade rice flour made it a suitable choice for blending with turmeric in powder form for subsequent sale in the market (refer to Fig. 1). Consequently, in alignment with the study's objectives, rice powder was chosen as a representative example of fraudulent adulteration in turmeric powder.

2.2 Preparation of the samples

During the sample preparation phase, turmeric was consistently blended with rice powder at five concentration levels ranging from 10% to 30%, with 5% intervals. This involved creating a set of 25 pure turmeric samples and adulterating each of them with rice powder at the specified concentration levels. Consequently, the total number of samples for image acquisition amounted to 150, comprising 25 pure samples and 100 adulterated samples, reflecting the varying concentrations from 10% to 30% at 5% intervals.



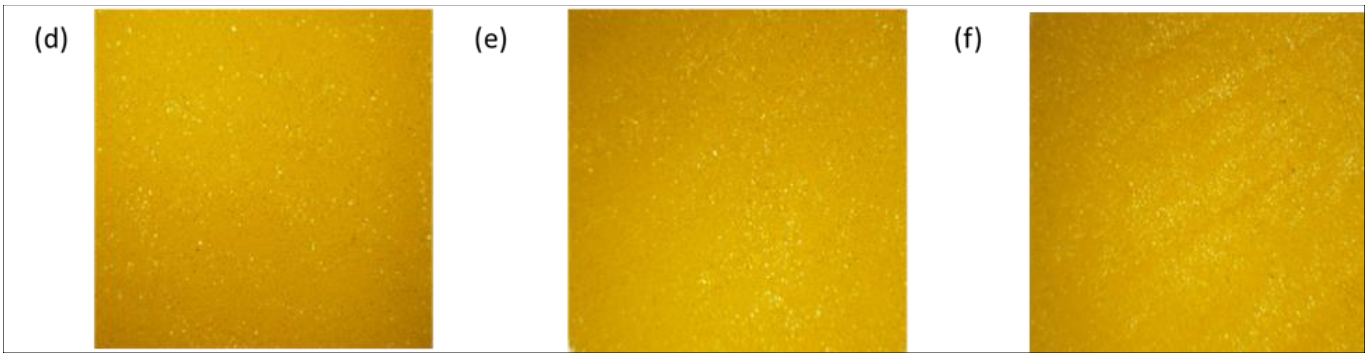


Fig 1: (a) Pure turmeric powder, (b) 10% adulterated with Rice powder, (c) 15% adulterated with Rice powder, (d) 20% adulterated with Rice powder, (e) 25% adulterated with Rice powder, and (f) 30% adulterated with Rice powder

2.3 Digital image acquisition system

In this study, standardized digital images were obtained using a custom-built light box constructed from 0.5 cm thick wood, measuring 40 × 40 × 20 cm, with a hinged front panel for easy sample replacement. A Nikon Z30-16_50MM digital camera with a 20-megapixel resolution was positioned in the upper center of the light box. The camera lens was mounted inside the box, maintaining a consistent 15 cm distance from the sample. To achieve uniform lighting, the lens was directed through a circular fluorescent light source. RGB digital images were manually captured and saved in JPG format. Fig. 1 illustrates images depicting turmeric adulterated with rice powder classes, offering a visual representation of various adulteration levels within the dataset. Throughout the image acquisition process, the camera settings remained constant. To generate the images, the position of the paper was adjusted and repositioned five times for each individual sample. This careful 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 setting, a dataset featuring six distinct classes of turmeric and turmeric mixtures was meticulously curated. The images of these blends underwent preprocessing using RGB color spaces and were subsequently subjected to classification through transfer learning algorithms. The model developed in this study serves as a comprehensive solution to the widespread issue of food adulteration, leveraging RGB color spaces and artificial intelligence architectures. The image preprocessing encompassed various techniques, including selecting a square region of interest, splitting, cropping, and converting them into RGB arrays. Each set of processed images then underwent classification using various deep learning algorithms. The model's performance was thoroughly analyzed through the utilization of a confusion matrix. Through a detailed examination of the classification results, the study aims to effectively address the problem of food adulteration, providing 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 the potential computational challenges posed by such large image sizes for Convolutional Neural Network (CNN) training, 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 enhancing computational efficiency, this approach aimed to enrich 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 crucial 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 commonly utilized in Convolutional Neural Networks (CNNs) to address the network's need for extensive annotated data for effective object classification. This technique aims to expand the dataset, thereby enhancing the accuracy of the CNN network. By introducing more diverse training data, the learning process is improved, and the risk of network overfitting is reduced. Essentially, data augmentation is a method employed in deep networks to supplement existing datasets by generating new training images from the current samples. This augmentation involves applying various 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 enhances the CNN's ability to generalize and learn robust features, ultimately leading to improved performance in object classification tasks. This translates to enhanced 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.

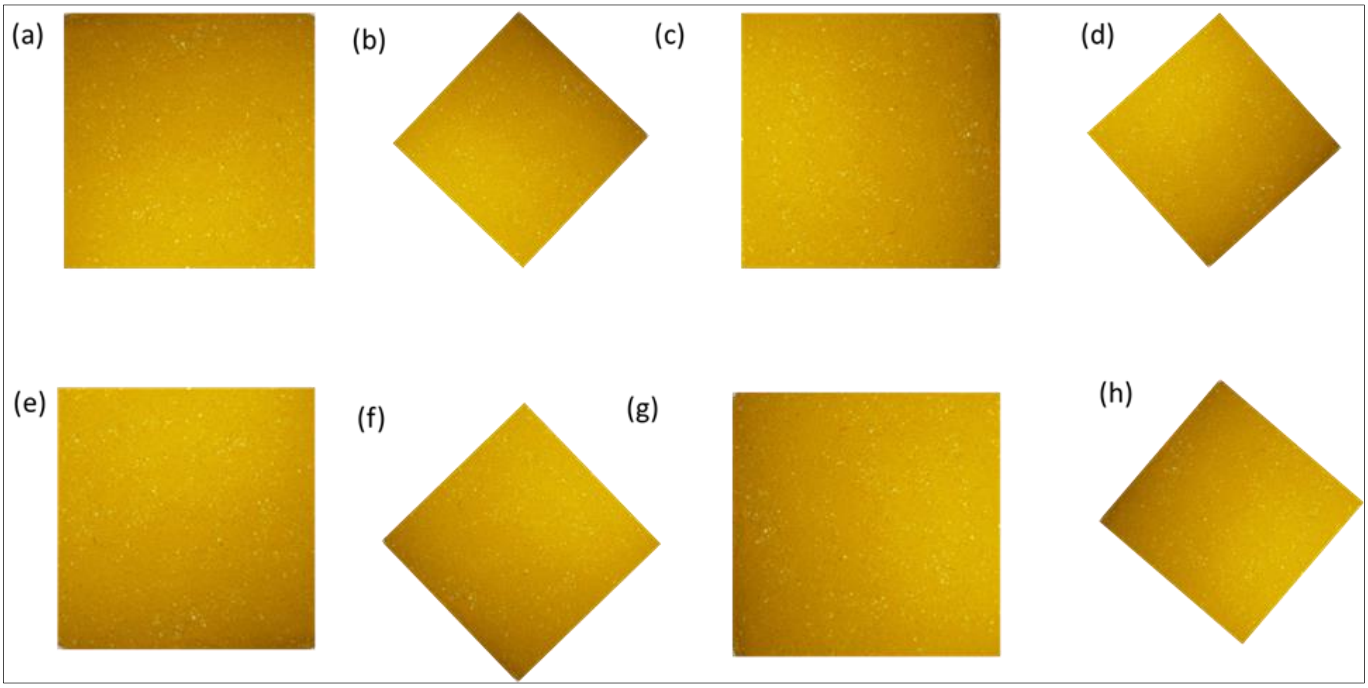


Fig 2: DA using image rotation: (a) Original image, (b) 45° rotation, (c) 90° rotation, (d) 135° rotation, (e) 180° rotation, (f) 225° rotation, (g) 270° rotation, and (h) 315° rotation

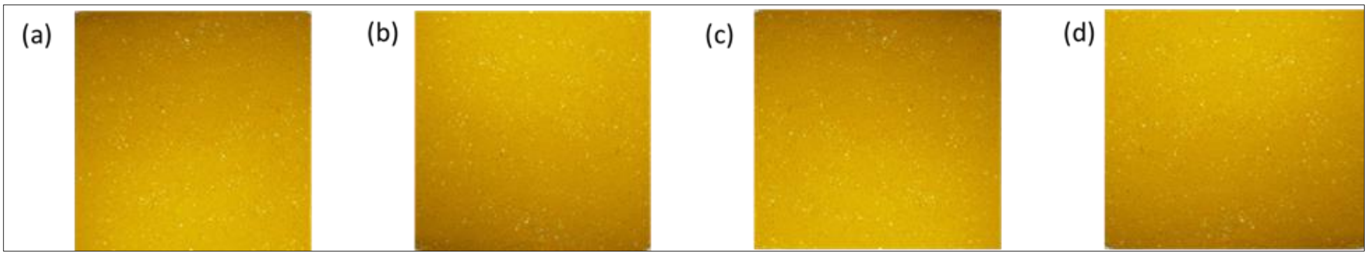


Fig 3: DA by image flipping: (a) Original image, (b) Flip horizontal, (c) Flip vertical, and (d) Flip horizontal and vertical

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). 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.

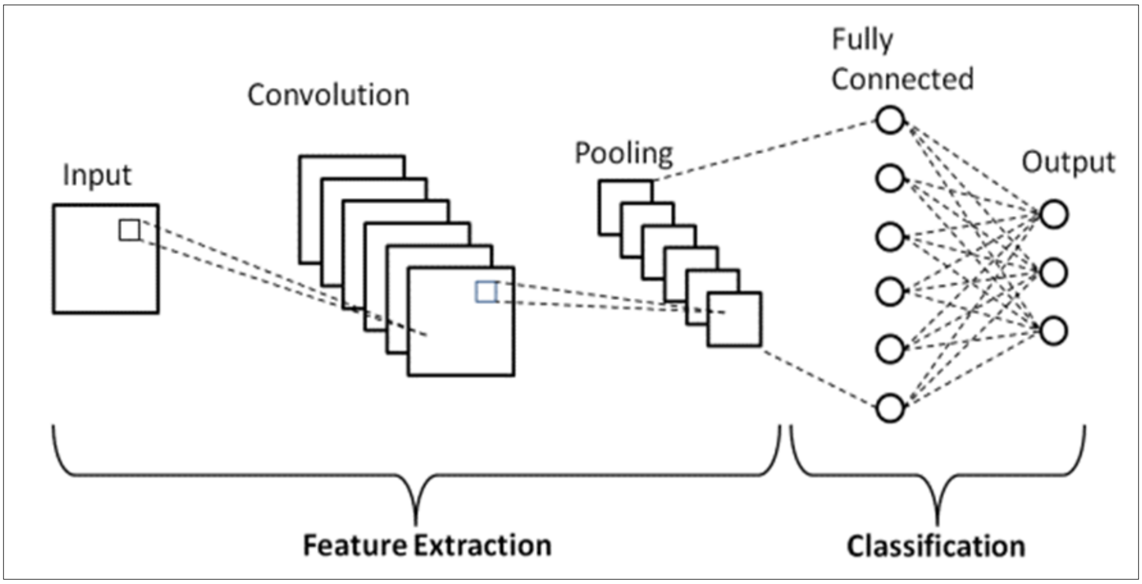


Fig 4: Common architecture of CNN (https://www.upgrad.com/blog/basic-cnn-architecture/)

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) [22]. 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 MobileNet-v2 model architecture was implemented due to its strong performance in various applications requiring image classification. MobileNet-v2, a highly efficient neural network architecture, is deployed for the innovative task of identifying rice flour adulteration in turmeric powder. Renowned for its lightweight design and suitability for mobile and edge devices, MobileNet-v2 proves to be a resource-efficient solution for this classification challenge. Trained on a diverse dataset encompassing authentic turmeric powder images and samples adulterated with varying concentrations of rice flour, the neural network adeptly learns discriminative features. Its depth wise separable convolutions contribute to a compact yet powerful model, ensuring accurate detection while minimizing computational demands. The MobileNet-v2's ability to maintain high accuracy in identifying adulteration showcases its practical applicability for on-the-go quality assurance in food products, particularly in scenarios where resource constraints are a consideration, emphasizing its versatility in real-world applications.

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) [23]. 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 all experiments were conducted within a Windows 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 influenced by its robust numerical computing capabilities and the availability of extensive toolboxes tailored for machine learning tasks. In the training phase, 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 assess 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. A batch size of 64 was set for training the CNN network for each group. The training process comprised 50 epochs, and the learning rate was fixed at 0.0001. These parameters were carefully selected to optimize the training process and achieve the desired performance in image classification.

Table 2: Optimized parameters for MobileNet-v2 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 current study involved the evaluation of 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 following equations:

- 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.

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

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 had 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 Rice 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 MobileNet-v2 CNN powdered turmeric classifier

The network architecture used is based on the MobileNet-v2 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 Rice 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 48 images of validation dataset, leading to a misclassification rate of 10%. confusion matrix shows the individual classification errors. As can be seen in confusion matrix, 3 sample of pure turmeric (class 1). 6 sample of 10% Rice flour adulteration (class 2), and 7 sample of 15% Rice flour adulteration (class 3), 11 sample of 20% Rice flour adulteration (class 4), 10 sample of 25% Rice flour adulteration (class 5), 11 sample of 30% Rice flour adulteration (class 6) were Misclassified. These facts combined with a nearly 90% accuracy suggest the high degree of reliability and robustness of the model.

Table 3: Specific misclassifications of the verification dataset.

Real class	Number of misclassifications	Predicted label	Accuracy of respective of class
Class 1	3	Class 2	100%
Class 2	6	3 as Class 1, and 3 as class 5	93%
Class 3	7	3 as Class 2, and 4 as class 5	96%
Class 4	11	4 as class 3, 3 as class 5, and 4 as class 6	84%
Class 5	10	3 as class 4, and 7 as class 6	91
Class 6	11	4 as class 3, and 7 as class 4	93

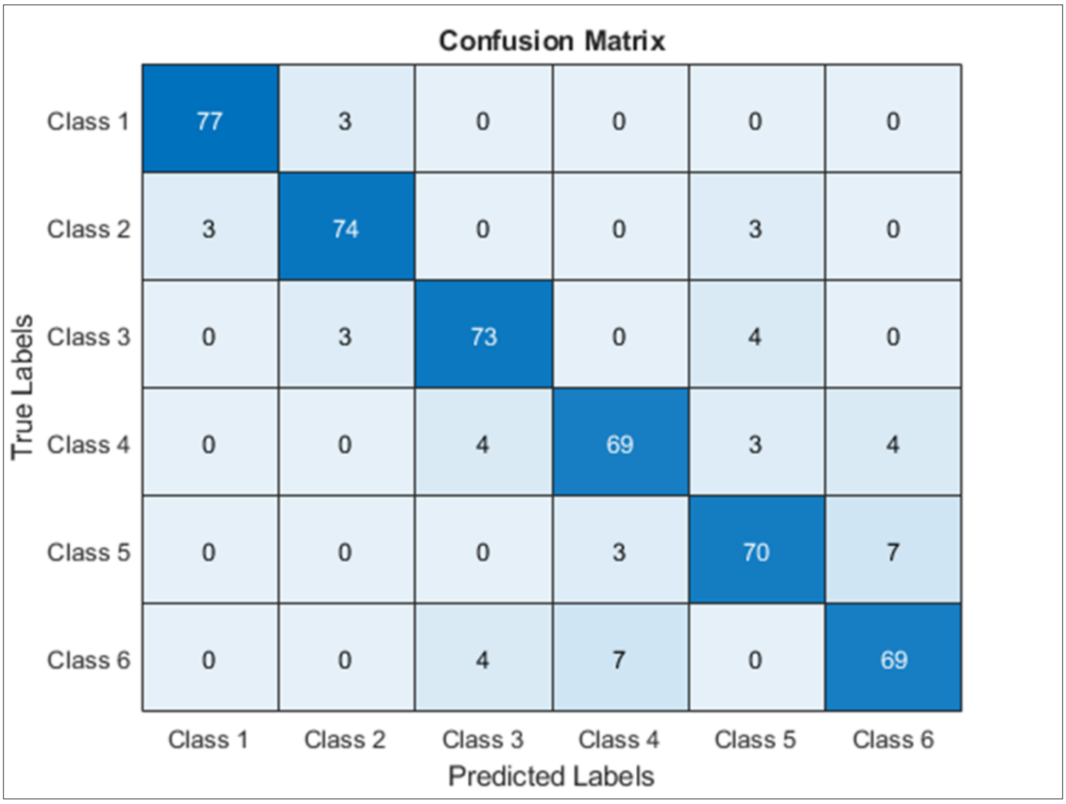


Fig 5: Confusion Matrix for Validation dataset

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 943% 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 422 images of validation dataset, leading to a misclassification rate of 5%. As can be seen in Table. 4, only in five cases an adulterated turmeric image has been classified as adulterated with different level, and no pure turmeric powder images has been misclassified. As can be seen in confusion matrix as well, all sample of pure turmeric (class 1) has been correctly classified with 100% accuracy as was in blind test data set. 7 sample of class 2, 4 sample of class 3, 16 sample of class 4, 9 sample of class 5, and 7 sample of class 6 has been misclassified. These facts combined with a nearly 93% 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

Table 4: Specific misclassification of the blinded samples.

Real class	Number of misclassifications	Predicted label	Accuracy of respective of class
Class 1	0		100%
Class 2	7	Class 5	93%
Class 3	4	3 as class 4 and 1 as class 5	96%
Class 4	16	7 as class 2, 8 as class 3, and 1 as class 6	84%
Class 5	9	1 as class 3, 2 as class 4, and 6 as class 6	91
Class 6	7	1 as class 3, 5 as class 4, and 1 as class 6	93

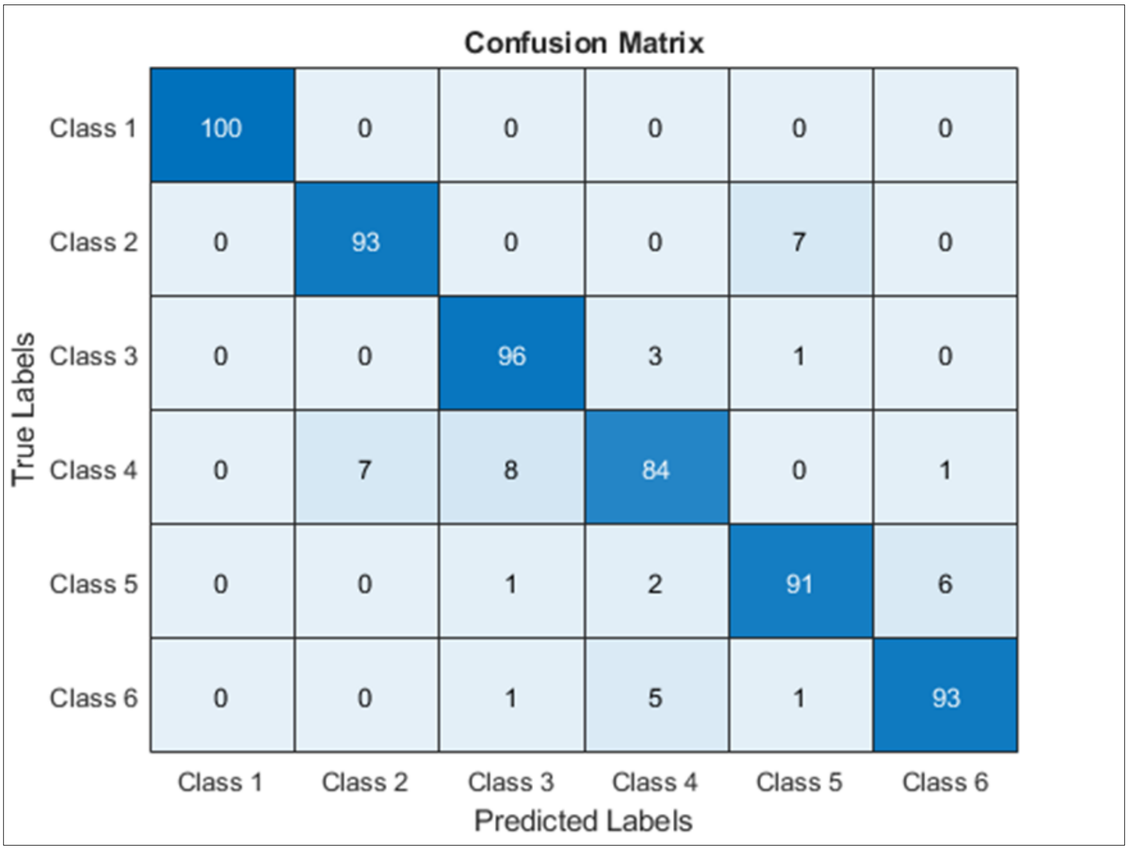


Fig 6: Confusion Matrix for Blind Testing dataset

4. Conclusions

In this study, a deep learning-based tool has been presented for quantifying Rice flour adulteration in turmeric powder samples based on RGB color value differences between pure and adulterated turmeric powder. The classification involved six types of powdered turmeric and their corresponding adulterations with Rice flour at concentrations (Pure, 10%, 15%, 20%, 25%, and 30%). A total of 600 images were captured and processed into 3000 original images 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 MobileNet-v2 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 90% during the validation phase. Moreover, when subjected to blind testing, the model exhibited a misclassification rate of 7%, 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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