Rice quality analysis using thermal images and Deep learning algorithm

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Abstract

Rice is one of the staple cereals which feeds nutrients to the consumers and serves major agricultural commodities in India. To improve the economy status and to serve good quality of rice to the consumers it is necessary to analyse the quality and also to avoid the adulterant. To gain extra profit, the vendor mixes the rice species varieties. Traditionally, rice grain quality evaluation carried by human visual perception which leads to time consumption and the results are not accurate. The proposed method deploys thermal image-based technique to detect the adulteration in Indian rice varieties using Deep learning algorithms. Indian rice varieties such as Karnataka Ponni and Pulungal Ponni are utilized for adulteration determination. Rice thermal images are processed through Convolutional neural network algorithm which results in classification accuracy of 95.83%.

Keywords

Thermal imaging, Deep learning, Convolutional neural network, Rice adulteration, Species discrimination

1. Introduction

Rice is the major staple food globally and nourishes over 21% calorific needs for half of the human population. Rice kernel global consumption rate increases for last few years and now 509.87 million metric tons consumed worldwide [1]. Due to increase in the consumption rate of rice there is possibility of fraudulent activity to gain profit and mix the rice sample varieties. Grading of rice with its quality is crucial factor to allot its market price value. The adulteration in rice samples can be determined through the physiochemical, morphological, physical appearances and functional properties such as DNA and protein-based analysis. These traditional based methods were expensive and not suitable for commercial scale determination of adulterants [2].

Conventional methods examine the quality of rice during milling with the experienced rice graders which consumes lot of time and milling is a destructive method. Several latest techniques such as Gas chromatography-mass spectrometry, High Performance Liquid Chromatography, spectral and spectral imaging, and computer vision methods are utilized to determine the adulteration in rice and paddy samples. Out of all conventional methods, imaging technique provides better solution to determine the adulterants in the food substances rapidly with low cost, accurate with portable sensor system measurements. The following literature work discusses image processing methods combined with Machine learning and deep learning model to determine the prediction of quality and classification.

1.1. Image processing techniques used for Rice quality analysis

Imaging processing methods are utilized to determine the quality of the rice samples using certain specific features from the images. Binary, grey scale, multispectral and color images are used for quality determination in food industries. The research work [3] employs Hyper spectral imaging for rice variety adulteration detection. Wuchang and Non-Wuchang rice are the samples used for adulteration determination. Six classes of adulterated rice mixtures are prepared with combination ratio in the range of (0-100%) by 20% increments. Spectral data are first processed with Piece wise Multiplicative

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Scatter Correction (PMSC) technique. After processing the information are forwarded to Support Vector Machine (SVM). Support Vector machine combined PMSC results correct classification accuracy of 99.20% for adulteration determination on rice varieties.

Headspace- Gas Chromatography-Ion Mobility Spectrometry (HGC-IMS) employed to determine the adulteration and classification of five various rice samples [4]. Baohan, Liannuo, Zhenghan, Nanjing and Luodao are the 5 sample varieties involved for adulteration and species determination. Semi-Supervised Generative Adversarial Network (SSGAN) utilized to classify the ion migration spectra and HGC-IMS images of rice samples. Rice samples are crushed and utilized for testing. Experimental analysis predicts rice species recognition at 98% classification accuracy with the SSGAN model. For adulteration determination the model employs high cost Wuchang and non-Wuchang rice samples 97.30% of adulteration determination achieved using HGC-IMS rice images with the SSGAN model.

The research work [5] analyses the quality of rice in the state of cooked by hydro thermal treatment. Three un-boiled rice varieties namely Gobindavog, Atap, new Atap and five parboiled varieties of rice namely IR36, IG-Basmati, Ratna, Basmati and Sarna are utilized for testing the quality features in the cooked condition. The rice kernel parameters such as Width (W), Length (L), Perimeter (P) and projected area (A) are measured using image processing method. The dimensional features such as shape factor and aspect ratio are measured to determine the grain appearance during hydrothermal treatment. The quality features help to eliminate the mixture of low-cost rice variety with the high-cost rice variety. Sarna, Basmati, Ratna, Ig Basmati and IR 36 are the parboiled varieties selected. Then New Atap, Gobindavog, Atap are the non- parboiled varieties chosen. The results analysed that cooked rice kernel aspect ratio increases and shape factor decreases with respect to time of hydro thermal treatment (boiling). Kernel variation also helps to determine the adulteration/mixing various rice varieties. With the consideration of market price prediction for rice kernels higher aspect ratio and lower shape factor obtains higher market price and vice-versa. The Aspect ratio of IG basmati is 3.75 and for Sarna it is 0.25. Similarly, Gobindavog the aspect ratio value is 2.25 and for Atap it is 1.4. with those aspect ratio values, concluded that Gobindavog in un-boiled rice variety obtains the best market price and quality factor than Atap. IG-basmati achieves better market price than Sarna in parboiled rice varieties.

A contrastive performance analysis [6] made with artificial neural network model and multi class support vector machine for classification of rice samples. Brown rice, basmati and ponni rice varieties images are chosen for experimentation. Shape and colour features chosen for classification. The test data set provides highest accuracy of 93.3% with Level sweep image transformation method of Artificial Neural Network (ANN). Another research work [7] focuses on classification of 5 Spanish rice flour varieties (ALB, AIS, ALV, AS, ABS,). The rice samples are grinded at different sizes such as 0.50-0.15 mm,1.36-0.50 mm, < 0.12mm and 0.15-0.12 mm to capture the images. Typical photographic camera used to capture the images of about 2700 and it is processed through Convolutional Neural Network (CNN). Results of the processed images can able to determine five different kinds of rice flours with 99% classification accuracy than the rice grain sample varieties. Another review work [8] discusses various Machine Learning (ML) algorithms such as Support vector Machine, decision tree, K-NN and deep neural network algorithms for the rice variety classification and prediction of adulterants. This work discusses the different attributes such as size, shape, color and area of brown and white rice samples. Compared to other ML algorithms Neural Network model achieves 100% of classification accuracy for 5 rice varieties.

The research work [9] involves determination of paddy adulteration between premium and commercially inferior paddy varieties. Premium Karnataka state paddy varieties such as Jaya, Mugad siri, PSB68 which is adulterated with commercially inferior paddy samples such as Budda, Mugad 101, Abhilasha, thousand ten and thousand one. The commercially inferior paddy samples are mixed at 15%, 10%, 20%, 25% and 30% of concentrated levels with the premium varieties. Total of 200 RGB images obtained from the adulterated samples and analysed through Back propagation neural network model. The model achieves maximum average 93.31% of classification accuracy in determining the adulterated paddy grains.

The research [10] proposes paddy grain variety classification based on the colour features extracted from YCbCr (Green (Y), Blue (Cb), Red (Cr)), HSV and RGB images. Mean, variance and range are the

Table 1
Methodologies employed to determine adulterants in rice and paddy samples.

Literature Work	Samples utilized	Type of Images / Algorithms employed	Accuracy
Estrada-Pérez, L.V., [12]	BLANCO, INTEG, VAPO and SD (species mixture)	Thermal images / CNN	98.8%
Bejo-Khairunniza, S., [13]	3 paddy types (MR220, CL2, MR219), [soil, pulses, mud, etc.,] (adulterants)	Thermal images / statistical analysis	100%
Ibrahim, S., [6]	Basmati, brown and ponni rice	RGB images / ANN & Multiclass-SVM	93.34%
Izquierdo, M., [7]	5 rice varieties (ABS, AIS, ALB, ALV, AS)	RGB images / CNN	99%
Ju, X., [4]	5 rice varieties (Baohan 1, Nanjing 9108, Luodao 998, zhenghan 10, linannuo 1)	HGC-IMS images / SSGAN	97.3%
Anami [9]	Paddy varieties (jaya, abilasha, Buddha, PSB68, Mugad siri, thousand one)	RGB Images / BPNN	93.31%

features utilized for classification determination. About fifteen paddy varieties are included with 3,000 images totally deployed for variety classification. A feed forward neural network model is employed to classify the grain varieties. Result says that average recognition accuracy of 94.33% obtained.

The moisture of rice grain / paddy samples has impact on its quality during storage and production. For this [11] research work low level moisture content rice grain sample range of (13-30%) is employed for experimentation. The work develops a portable single band (1450nm) sensor for rapid detection and real time quality monitoring of the rice grain. The spectral information is obtained from the NIR spectroscopy. Competitive Adaptive Reweighted Squares (CARS) and Partial Least Squares (PLS) model utilized to analyse the sample spectral data. The sensor performance evaluated for the low-level moisture content paddy sample which achieves coefficient of determination as 0.936.

Table 1. describes spectroscopic and imaging techniques and algorithms employed to determine the adulterant and classification among the rice and paddy samples. The system model utilizes geometrical features and colour feature to predict the quality and species classification among the rice samples varieties. Thermal imaging technique combined with deep learning model achieves highest classification accuracy in determining the adulterants and classification of species rice varieties. However, those methods utilize rice flour samples for classification.

Among the other imaging methods, thermal imaging provides better determination of objects due to the individual objects infrared measurement and also it can effectively penetrate through aerosol, smoke etc than the visible light radiation. Thermal imaging-based rice quality analysis are discussed in the related work.

1.2. Related work

Thermal imaging refers to non-contact, non-destructive measurement which detects the Infrared radiation/heat emanate by an object. Thermal imaging serves as a diagnostic tool in a reliable way for adulteration examination and safety inspection on the food products. The mid- wave infrared regions (3000-5000nm) exhibits better sensitivity and which is most preferable in food industries [14]. With the variation in individual temperature measurements the adulteration in the rice varieties can be easily determined using thermal imaging methods. Adulteration among various rice sample varieties is determined using thermo graphic camera is performed in [12] research work. Four adulterants namely BLANCO, INTEG, VAPO and SD and one pure sample SEMI has chosen for adulterant identification. The rice grains as well as its flour samples are employed for adulteration determination. The sample placed on the transparent spectroscopic cuvette which is placed on a closed container maintained at 35.5 °C for 20 minutes. Thermo graphic images are obtained for the rice and its respective flour samples. Thermal images are processed with Convolutional Neural Network Model for classification of rice varieties.99% classification accuracy is achieved to discriminate the pure and adulterated samples.

The adulteration in paddy samples can be detected using thermal imaging based on the quality features such as immature condition, foreign materials such as chaff and moisture content are presented [13]. From the acquired thermal images, Pearson correlation analysis is performed to determine the relation between moisture content and thermal index of paddy sample. Results shown that there exists a stronger relationship between maturity and thermal index at (correlation analysis) r= -0.948 and r= 0.896 significance rate achieved between moisture content and thermal index. R2=0.92 obtained to determine the moisture content and for predicting maturity is analysed as R2=0.90. It also produces 100% accurate results for identifying the chaff (Pulses) in the paddy samples.

Another research work [15] designs an automated methods which are Discrimination on RGB Images (DRI) and Discrimination on Thermal Images (DTI) to distinguish the unfilled and filled panicles of rice grain samples using thermal and RGB images. Fifteen rice panicles of various genotypes chosen for experimentation. Various color space information is obtained such as "Lab"," HSI"," HSV," RGB" and "LUV". Discrimination based on thermal imaging achieves absolute errors of 2.66% for filled grains and 11.38% for unfilled grains which is better than RGB method of discrimination. The method employed shows better results in discriminating rice grain panicles of various genotypes using thermal images than the RGB images.

In general, RGB and thermal images are used to classify the rice varieties and also to determine the adulteration. The images are obtained in a controlled environment and the samples may undergone for pre-treatment before obtaining the images. Devices deployed to acquire the images are costlier and few are not portable. To overcome these drawbacks The proposed method employs deep neural network for classification of adulteration in rice sample varieties. Proposed work Contribution are stated as follows:

1. The work focus on adulteration determination of Indian rice varieties in such way to classify the high-cost rice sample adulteration with the low-cost rice samples.
2. Thermal images are obtained at three different distance measurements (5cm,10cm,15cm) from the surface of the sample.
3. Image augmentation is carried out to improve the performance and train the system model.
4. CNN model predicts the adulteration with 95.83% classification accuracy.

Moreover, thermal imaging technique achieves 100% classification accuracy in adulteration determination but, the work [13] involves various other physical appearance adulterants not on same rice variety adulteration.

The following section of the article is aligned as follows. Section 2 describes the devices and methods employed for classification; rice sample preparation followed by the architecture of convolutional neural network model. Section 3 delineates the results obtained from the CNN model and comparison chart. Finally, the article is concluded with related future work.

2. Methodology

This section delineates thermal image acquisition and processing through convolutional neural network model for adulteration classification. Thermal images are acquired using thermal imager named FLIR -8E series with the average temperature range from 31.3 to $35.4°F$. Thermal imager has the pixel resolution of (320×240=76,800) with the sensitivity of $< 0.06°C$. It has 3-inch color display to view the images and the field of view is $45° \times 34°$. Thermal camera detects radiation in mid-IR wavelength ranges from $3\mu m$ to $5\mu m$ and Long-IR wavelength ranges from $7.5\mu m$ to $14\mu m$.

Figure 1 shows the sequence of steps from image pre-processing to the classification of adulteration. Indian rice varieties such as Karnataka Ponni and Pulungal Ponni are employed for adulteration determination. First all the pure rice sample thermal images are acquired. Then the samples are mixed at

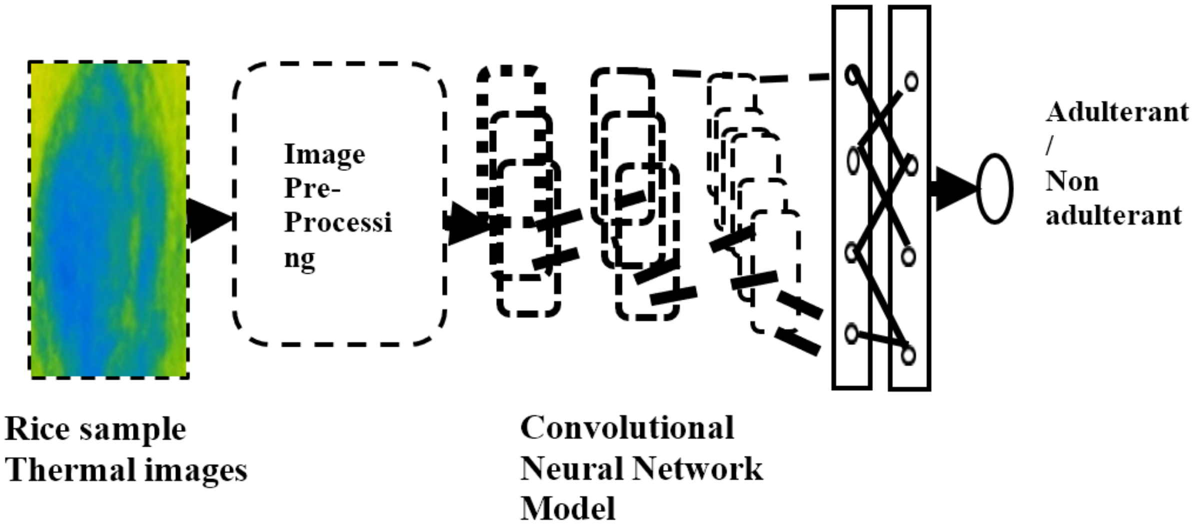

Figure 1: Block diagram for rice adulteration determination using Convolutional Neural network model.

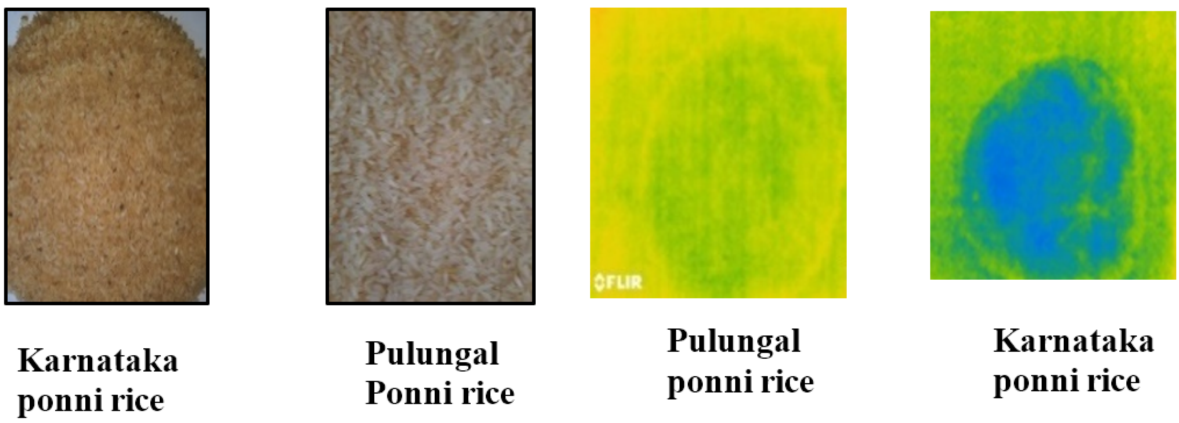

Figure 2: RGB and thermal images of rice samples.

various concentrations which is given in table 5. The images are acquired for each mixture rice samples. RGB and thermal images of pure and mixture rice varieties are shown in Fig. 2. The acquired adulterated sample images are in a smaller number of 27 images totally, to train and classify the adulteration with convolutional neural network model it is required to augment the input images. Augmentation helps to boost the performance of the model. The acquired and augmented images are given to the convolutional neural network model to train and classify the adulteration.

2.1. Sample preparation

Indian rice varieties such as Karnataka ponni and pulungal ponni, are deployed for experimentation. The rice varieties utilized and its concentration of adulteration are listed in Table 2, while Table 3 discusses the total number of thermal images acquired from the pure and adulterated samples with its respective distances and modes of lightning. The images are captured in three different lighting conditions such as bright mode, medium dark and ambient mode. It is also captured at three different height measurements such as 15cm, 25cm and 30cm distance from the surface of the rice sample. Distance measurement are marked with ruler.

From Table 3 only 27 image samples of pure and adulterated rice samples are obtained. Data

Table 2
Sample preparation.

Rice sample varieties	Mixture level of concentration (in grams)
Pulungal Ponni (PP) - Rs.35/-(PP 35/-)	Pure (100 grams)
Pulungal Ponni (PP) – Rs.50/-(PP 50/-)	Pure (100 grams)
Pulungal Ponni (PP) –Rs. 55/- (PP 55/-)	Pure (100 grams)
Pulungal ponni rice mixture	(125 PP 35/-+15 grams PP55/-) [140 grams mixture]
Pulungal Ponni (PP) and Karnataka Ponni (KP) rice mixture	Mixed (125(PP 55/-+PP 35/-)+100 KP 45/-) [225 grams mixture]
(220g PP 50/-+80 g PP 35/-) 280 grams mixed	Mixed (220g PP 50/-+80 g PP 35/-) [280 grams mixture]

Table 3
Number of images acquired from the pure and adulterated samples.

Rice sample Varieties	Distances measured from surface of rice sample	Modes of lighting conditions	No. of thermal, images acquired per sample
Pulungal ponni Rs.35/-	15cm	Bright	3
	25cm	Medium	
	30cm	Ambient	
Pulungal ponni Rs.50/-	15cm	Bright	6
	25cm	Medium	
	30cm	Ambient	
Pulungal ponni Rs.55/-	15cm	Bright	6
	25cm	Medium	
	30cm	Ambient	
(125 pp35+15 grams pp55) 140 grams mixed rice	15cm	Bright	6
	25cm	Medium	
	30cm	Ambient	
(125g (pp55+pp35) +100 KP45) 225 grams mixed rice	15cm	Bright	3
	25cm	Medium	
	30cm	Ambient	
(220g pp50+80 g pp 35) 280 grams mixed rice	15cm	Bright	3
	25cm	Medium	
	30cm	Ambient	
Total number of samples obtained			27

augmentation is carried out to increase the number of images by flipping, cropping, rotating and lateral shifting. Thus, augmentation helps in generating 396 pure and 528 adulterated samples and which is utilized to train the Convolutional Neural Network model.

Table 4
Design of convolutional neural network model.

Input dimension	Output dimension of 1st Convolutional layer	Output dimension of 1st Max Pool layer	Output dimension of 2nd Convolutional layer	Output dimension of 2nd Max Pool layer	No. of neurons in Fully connected layer+ SoftMax	No. of neurons in Output layer
$320{\times}240{\times}3$	$237 \times 237 \times 3$	$40 \times 40 \times 8$	$38 \times 38 \times 3$	$13 \times 13 \times 3$	1×507	1

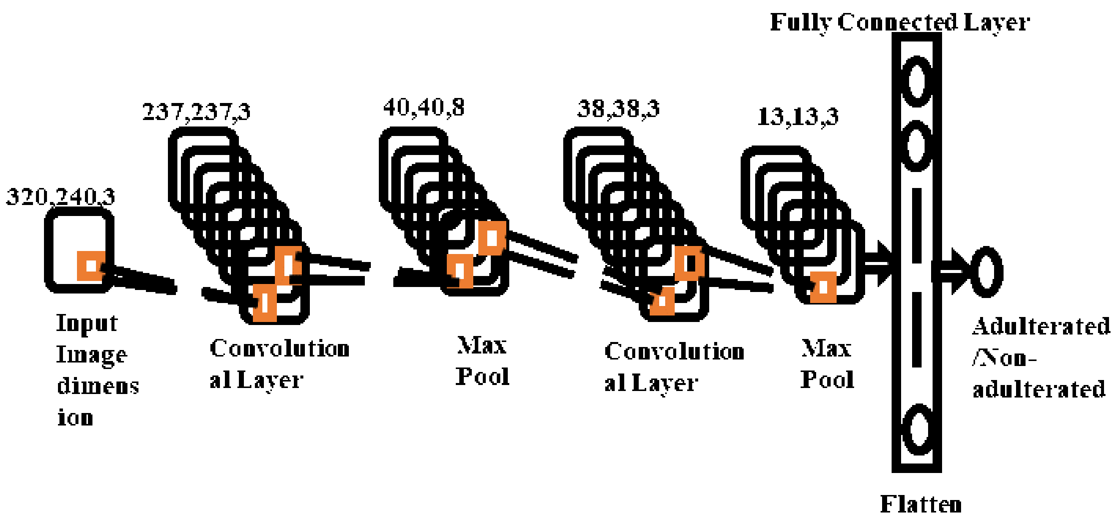

Figure 3: Convolutional neural network architecture.

2.2. 2.2 Convolutional Neural Network Model

The image size of dataset is $320 \times 240 \times 3$ (320×240-pixel size, 3 channel). Figure 3 illustrates the Convolutional Neural network architecture. CNN consists of mainly three layers. Convolutional, pooling and fully connected layers. Convolutional layer extracts the features from training dataset by means of filters of size 3×3. The input image (matrix) undergoes for convolving with striding of 1 and padding 0. After feature map extraction in the convolution layer, it further undergoes max pooling to reduce the mapping and to extract the maximum input matrix value. By performing these calculations, the input image size will be reduced, but still maintaining the representative information.

Rectified Linear Unit (ReLU) is the activation function utilized in Convolutional Neural Network model.

$$R\left(x\right) = \begin{cases} x,\, x > 0 \\ 0,\, x \leqslant 0 \end{cases} \tag{1}$$

Finally, the third layer of CNN is fully connected layer is a supervised neural network which recognize the features obtained from the previous layer. Fully connected layer ($1 * \times 507$) classify the images at the output with soft max to determine whether adulterant is present or not. The SoftMax allows classification of image with its probabilistic value prediction.

Table 4 lists the number of layers involved to construct the convolutional neural network architecture.

Table 5
Evaluation Metrics.

Performance Metrics	Accuracy
Binary classification	95.83%
Precision	89.29%
Recall	96.15%

3. Results and analysis

The section discusses the results of Convolutional neural network model for the adulteration determination. Total images dataset is divided into three categories such as 75% for training, 15% for testing and 10% for validation. During training the datasets are used to analyse the errors and optimize the learning parameters. The results arrived are listed in table 5.

Table 5.Shows that binary classification of adulteration achieves 95.83% accuracy to discriminate the pure and adulterated varieties.

Compared to Table 1, the proposed work utilizes samples from Indian rice varieties (Karnataka ponni, pulungal ponni), and by using Thermal images / CNN, the accuracy of 95.83% is achieved.

The rice species adulteration is identified with thermal images [12]. Five rice sample varieties are chosen for experimentation. The rice grain and its flour samples are employed for testing the adulteration. Thermal images are obtained with the maintained average temperature of $35°C$ and maintained at 25cm away from the surface of the sample. Video is recorded during experimentation later the images are extracted for further processing. 4grams of samples employed for testing. Thermal images are processed through Convolutional neural network model which achieves 99% of classification accuracy. The samples are placed in a cuvette and maintained a closed environment. Moreover, it employs rice flour samples for the adulteration classification.

In the research work [4] determines adulteration between two china rice and its flour samples with the images of Headspace- Gas Chromatography-Ion Mobility Spectrometry. The work also determines the variation in ion mobility spectra of the flour samples. the images are processed through Semi-Supervised Generative Adversarial Network (SSGAN) for classification of adulteration which achieves 97.3% of accuracy.

The classification of five Spanish rice samples with the typical photographic camera images [7]. The rice samples are grinded to various sizes and the images are obtained from the flours. Images are processed with Convolutional neural network model and achieves 99% classification accuracy to determine the rice varieties. The whole rice and its flour sample images are utilized in this work for variety classification. Results analysed that destructive sample (i.e., flour) performs better classification accuracy of 99% than the whole rice sample which achieves 93% of classification accuracy.

The proposed model obtains adulteration classification for Indian rice varieties with the thermal images. Thermal images are processed with CNN model which achieves 95.83% adulteration determination in the rice samples. This method proves better classification on adulteration determination among the rice varieties. The model works better even for different distances between the camera lens and sample surfaces.

When compare to the existing works, the proposed work utilized whole rice sample not grounded flour sample. The work presents adulteration determination of rice varieties. The images are obtained at various three different measurements (5cm, 10cm, 15cm). The experimental setup and sample pretreatment are not required for the proposed system design.

4. Conclusion

Quality assessment and process control is the major task need to be monitored for all the food materials for its high level of demand. One of the staple cereal crops is rice in most of the countries. The proposed work utilizes thermal imaging technique to determine the presence of adulteration in rice grain samples. Indian rice samples such as Karnataka ponni and varieties of pulungal ponni are utilized for adulteration determination. Thermal images are obtained and processed through convolutional neural network model which achieves classification accuracy of 95.83%. The work can be extended to determine adulteration in mixing more than two rice samples.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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