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Deep Neural Network-Based Grain Adultration Detection

Prof.Rajashekhar S A[1]

Abhishek GM[2], Gundappa[3], Jeswanth A L D[4], Kamanna[5]

Assistant Professor, Computer Science, East West Institute of Technology, Bangalore, India [1]

Student, Computer Science, East West Institute of Technology, Bangalore, India[2-5]

Abstract: Food is a fundamental requirement that gives our bodies the nutrition they need. Given that food grains are being adulterated at an increasingly rapid rate, food quality is the most important thing to be examined. The current quality assessment process is laborious and prone to human mistake (unknowingly or intentionally). This will have an impact on the farmer who depends on the farm for his daily sustenance because they don't receive a fair price for their years of combined labour. Additionally, Manual Assessment promotes the adulteration of food grains, misleading consumers by combining inferior grains or compounds that mimic grains while generating high margin profits.

Keywords: Grain adulteration, Pre processing of image, Brightness equalization, Edge detection, Image segmentation, Feature extraction of image, Color feature extraction, Classification of Extracted image,Support Vector Machine (SVM), k-Nearest Neighbor (k-NN)

I. INTRODUCTION

Grain adulteration and consumption for the production of low-cost grains have a very long history in India. Indian toxin industries still rely heavily on manual labour and have little in the way of automation or mechanisation. When human inspection is misleading society and selling low-quality food, automation is absolutely important.This project demonstrates an automatic grading system that uses digital image processing to process grain images and categorise the grains into Good, Average, and Bad classes by taking into account predetermined values. The grains, weed particles, and other foreign materials are easily recognised. To accomplish this, train the system with a series of photos, and then use the results to test the input image. It can automate a process that is accurate, factual, time-saving, and life-saving in order to prevent the harmful disease that will be brought on by adulteration. Food is a fundamental requirement that gives our bodies the nutrition they need. Given that food grains are being adulterated at an increasingly rapid rate, food quality is the most important thing to be examined. The current quality assessment process is laborious and prone to human mistake (unknowingly or intentionally). This will have an impact on the farmer who depends on the farm for his daily sustenance because they don't receive a fair price for their years of combined labour. Additionally, Manual Assessment promotes the adulteration of food grains, misleading consumers by combining inferior grains or compounds that mimic grains while generating high margin profits. Grain adulteration has an impact on both society and people.In modern civilization, everyone wants to be successful, but nobody stops to consider the impact of human being

II. RELATED WORK

A. Deep Neural Network-Based Sorghum Adulteration Detection in Baijiu Brewing Suppliers may substitute commercially inferior japonica sorghum for glutinous sorghum during the Baijiu brewing process, which could have an impact on the quantity and quality of the finished product. Sorghum adulteration detection in the Baijiu brewing process is now done manually in China through sampling and observation, which heavily relies on the worker's experience. In this paper, we suggested a method to recognize grain kinds , determine the ratio of adulteration using sorghum photos as input and combining processing of images using deep neural networks. The implementation of the deep neural networks for sorghum grain detection and adulteration ratio computation uses two CNN derivative networks, namely ResNet and SqueezeNet. On the test set, the ResNet and SqueezeNet-based models' classification accuracy was 93.34% and 87.98%, respectively. For the estimation of the adulteration ratio, the root mean squared error (RSME) is 4.95% and 7.73%, respectively. Accordingly, the mean absolute error (MAE) is 4.20% and 6.29%. The suggested pipeline can quickly and non-destructively identify adulterated raw materials used in industrial production, which supports the digital transformation of industry and increases productivity. B. Fruit quality detection using opencv/python The computer vision-based solution for fruit quality identification is presented in this research. This technology is increasingly being used in the fruit business and in agriculture. Rapid, economical, sanitary, consistent, and objective assessment is made possible by computer vision systems. Fruit's look is one of its key qualitative attributes. In addition to affecting their

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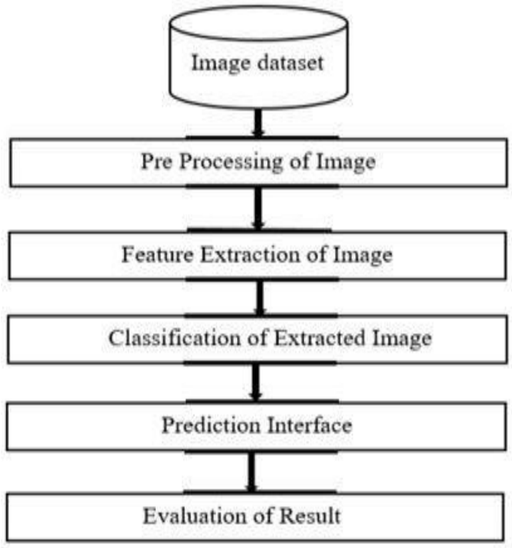
market worth, consumer preferences, and choice, appearance can also, to some extent, affect their internal quality. Tomato fruit is employed in this paper as the output. There are numerous varieties of tomatoes; for this research, 225 tomato species were chosen because they are available year-round. India is a nation based on agriculture. India produces a wide variety of fruits and vegetables. India ranks second in output behind China in production of fruit.

The industry found it challenging to categorise the quality of fruits using the conventional way, so an image processing technology was developed to categorise the fruits. India's economy is reliant on agriculture, hence automation in this sector and other associated industries is crucial. Fruits go through a number of post-harvest processes, including washing, sorting, grading, packing, storage, and shipping. Israel and Australia, two agriculturally productive nations, have demonstrated active usage of this new technology, and the Indian fruit industry needs to catch up. Farmers, particularly those from India, who cannot afford the cost of modern fruit processing facilities are among the project's primary benefactors. Fruit's look is one of its key qualitative attributes. Their appearance affects not just their commercial value but also their preferences of the consumer, as well as to some extent, their interior quality.

III. PROPOSED METHODOLOGY

Deep neural network classifiers are often trained via supervised learning, which involves gathering a lot of labelled data. The quality and size of the dataset significantly affect classification performance, regardless of network structures and various model types. As a result, the collection of unique photos is essential to the overall endeavour.



A. PRE PROCESSING OF IMAGE

Image processing is a method where a machine examines the image and processes it to provide you with more information. Image processing can typically be done in a variety of ways. You can do it with the use of machine learning, or you can use it if you require detailed processing. A supervised method of processing pictures is deep learning. The data that has been processed can be used for a variety of purposes.

a. Brightness equalization

Uneven lighting during image acquisition led to shadows in the backdrop, which would hinder edge recognition and also produce variations in the histogram distribution of colour space between segmented images, lowering the homogeneity of the data. As a result, the backdrop must be located, removed, and the brightness of the image adjusted.

b. Edge detection

To reduce image noise, convert the image to grayscale and apply low-pass filtering techniques like Gaussian blur. Consider using morphological techniques like dilation and erosion to separate adjacent sorghum grains. Then, using the Canny edge detector, identify the outer contours of each connected component. For a grey scale gradient, the equivalent low and high thresholds are 100 and 200, respectively.

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c. Image segmentation

Utilize polygons to using, approximately, the contours the Douglas-Peucker algorithm . Determine the smallest up-right bounding rectangle for each polygon, then manually define width and height limits to filter out noise points. In practise, these thresholds were set at a minimum of 1700 pixel2. We segmented each granule using a square with a predetermined side length (140 pixels) in order to maintain the size information of the grains. The square's centre coincides with the boundary rectangle's, and its side length is more than the sum of the rectangles' long sides.

B. FEATURE EXTRACTION OF IMAGE

People can tell if a grain is adulterated from an image sample by its color and textural characteristics. Due to the various shapes and color of individual grains, adulteration among different grains will result in a considerable alteration in the chrominance and textural characteristics of the image sample. To achieve the thorough adulteration level classification process, statistical chrominance data and textural features are evaluated. The color and texture aspects of the photos are extracted as features in the current work.

a. Color feature extraction

The color channels of the work photos must first be separated before the color feature extraction can begin. In this, the R, G, and B components of the images in the RGB color model are separated.

b. Texture feature extraction

The textures of grain samples are frequently unpredictable owing to differences in orientation, scale, uneven illumination, and other visual parameters of individual grains. This has affected the inclusion of spatial scale, orientation, and grayscale invariance when extracting texture features from grain sample images.

C. CLASSIFICATIN OF EXTRACTED IMAGE

When a computer analyses an image, it can determine the "class" that the image belongs to.

a. Back Propagation Neural Network (BPNN)

Because of its simplicity and effectiveness in using a large training data set, multilayer back propagation neural network has been used as one of the classifiers in the current work.

b. Support Vector Machine (SVM)

A potential linear classifier based on the idea of decision planes that specify decision boundaries is the multi-class Support vector machine (SVM). A decision plane is a diagram that distinguishes between a collection of objects with various class memberships.The training data is used to create a hyperplane that divides pixels into distinct classes.

c. k-Nearest Neighbor (k-NN)

An ad-hoc classifier called the k-nearest neighbour (k-NN) algorithm is used to categorise test data according to a distance metric. In the current study, distance is utilised to classify images with a desired range of values for the neighbourhood parameter "k" (k = 1, 2, 3...). The dataset and the ultimate application both influence the selection of the "k" value, which is crucial to the performance of the classifier.

IV. PERFORMANCE ANALYSIS

According to the methods utilised in this work, the total grain adulteration level classification performances of the individual and combination color-texture features are examined. The ratio of correctly categorised sample grains to the total number of sample grains taken into consideration is used to calculate the % accuracy of the adulteration level classification.

A. Precision, Recall & Accuracy

It is possible to observe the comparative study of detection using different classifiers. Precision is a classification model's capacity to pinpoint only the pertinent class. A classification model's recall is its capacity to locate each and every pertinent example in a dataset.

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TABLE I COMPARISON MATRIX

Figures of Merit	CNN	FNN	kNN	SVM
Precision	95.67%	94%	96.61%	97.37%
Recall	100%	95.23%	90.47%	96.57%
Accuracy	98.33%	95.40%	93.30%	98.71%

V. CONCLUSION

The potential of colour and texture characteristics is shown by classifying adulteration degrees (%) from photos of a mixed grain sample.We presented a unique adulteration detection pipeline for grains based on deep neural networks. We used a series of instruments, including a vibration base and CMOS camera, to gather the dataset. From the original photos, we split individual grains and input them into networks. Using morphological and colour data vectors from sorghum grains, deep neural networks outperformed SVM in terms of accuracy and generalizability. The suggested technology has the potential to further the automation of the brewing industries and boost production effectiveness while allowing for quick, non-intrusive, and inexpensive adulteration detection of brewing supplies.

REFERENCES

[1] Shanglin Yang , Yang Lin , Yong Li , Defu Xu , Suyi Zhang , And Lihui Peng, “Deep Neural Network-Based Sorghum Adulteration Detection In Baijiu Brewing” Received 15 May 2022; Revised 23 June 2022; Accepted 25 June 2022. Date Of Publication 12 July 2022; Date Of Current Version 25 July 2022.
[2] Miss. Supriya V. Patil1, Miss. Vaishnavi M. Jadhav, Miss. Komal K. Dalvi, Mr.B.P.Kulkarni Fruit quality detection using opencv / python May 2020.
[3] Shaikh Rakhshinda Nahid M.Ayyub, Aarti Manjramkar. Fruit Disease Classification and Identification using Image Processing, Proceedings of the Third International Conference on Computing Methodologies and Communication (ICCMC 2019) IEEE Xplore Part Number: CFP19K25-ART; ISBN: 978-1-5386-7808-4.
[4] Astha Ratley, Mrs. Jasmine Minj, Mrs. Pooja Patre Automated recognition and classification of adulteration levels from bulk paddy grain samples, Received 8 February 2018 Received in revised form 30 August 2018 Accepted 5 September 2018 Available online 6 December 2018.
[5] Prince Sahaya Brighty1, G. Shri Harini2, and N. Vishal Detection of Adulteration in Fruits Using Machine Learning 2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)|978-1-6654-4086-8/21/31.00 ©2021IEEEDOI:10.1109/WISPNET51692.2021.94194 02.