Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 45 (2024), No. 4, pp. 1005–1015
DOI : 10.47974/JIOS-1623

Image based identification of millets using fusion of Hu moments and LBP

Swati Shilaskar *
Shripad Bhatlawande †
Prapti Duddalwar §
Sakshi Jaiswal ‡
Dipali Kadam @
Kaustubh Chavan #
Department of Electronics & Telecommunication Engineering
Vishwakarma Institute of Technology
Pune 411037
Maharashtra
India

Abstract

The identification of millets is important for ensuring food security and sustainable agriculture. This work proposes a novel approach that combines computer vision techniques with ML algorithms to recognize different types of millets based on their visual features. These features are used to train a ML framework that can classify millets with high accuracy. The proposed system used 3 samples of millets which include jowar, bajra and raagi. Based on their shape and texture features the model predicts the millets using various machine learning algorithm. The accuracy of the proposed work is 92% using random forest classifier.

Subject Classification: *Primary 62C12, Secondary 62H30.*

Keywords: *Millets, Contour detection, Local binary pattern, Hu moments.*

* *E-mail:* `swati.shilaskar@vit.edu (Corresponding Author)`
† *E-mail:* `shripad.bhatlawande@vit.edu`
§ *E-mail:* `prapti.duddalwar21@vit.edu`
‡ *E-mail:* `sakshi.jaiswal21@vit.edu`
@ *E-mail:* `dipali.kadam21@vit.edu`
# *E-mail:* `mahendrakumar.kaustubh21@vit.edu`

1. Introduction

The agriculture industry has been a critical component of human civilization since its inception, and millets have been an essential source of food for millions of resource-poor farmers in India. Millets have an important part in the country's ecological & financial security, as they are high in nutrients and fiber. They are a staple food for more than 90 million people in Asia. They need 40% less energy to process, flourish in half the time of wheat, and use 70% less water than rice. [1] Millets contain minerals such as calcium, iron, zinc, phosphorus, magnesium, and potassium, along with dietary fiber and vitamins like folic acid, vitamin B6, beta-carotene, and niacin. Millets also have a promising future in the functional food industry due to their superior nutrient profile and hypoglycemic properties. The primary aim of this project is to develop a millet identification system that can support visually challenged individuals by identifying millets based on their size, color, and other visual features, thereby making their lives easier. Such a system could significantly improve the efficiency and accuracy of millet identification, benefiting farmers, researchers, and policymakers alike.

2. Literature Survey

Grain detection using machine learning techniques has been studies in literature. This model may be employed to locate and count pictures in a range of complicated backdrops at different vantage points and perspectives. This model is a useful tool for identifying and counting wheat grains, with a false-positive rate that is less than 3% and an operating duration of less than 2s [1]. The experimental data is used to evaluate the algorithms. As predicted, experimental results shows that HOG features perform better than partially based on color GLCM features [2]. Image enrichment techniques raise the rate of identification accuracy [3]. The redundancy of Hu attribute is substantially larger than that of morphological traits. Soft computing based feature descriptors are suggested to improve identification rate [4]. Leaf classification is performed using deep learning [5]. According to experimental findings, GLCM based features can be employed for haploid maize seed recognition, and combining their average values yields better outcomes. The results show that different types of dry beans can be automatically classified using the classifier [6]. This research compares the effectiveness of three distinct machine learning techniques using rice photographs and attributes extracted from the photographs. The CNN approach instantly analyses images and makes use of various hidden features including size, color, and other aspects, thus the classification success rate is 100% [7]. Fine-tuned CNNs achieved accuracy ranging from 94% to 95% for classification of wheat grain images compiled from diverse production zones [8]. The SVM algorithm is used on the dataset of different kinds of rice and performance parameters namely precision, recall, F1-score, and support values, are displayed [9]. The two distinct classes of pumpkin seeds using 5 machine learning techniques were identified [10]. The 98% accuracy rate by the proposed CNN-based model properly classifies 15 different wheat types [11]. A CNN for classifying the kernels from scanned pictures gave accuracy rate as 99.52%. On the datasets of rice kernels, the deep learning architecture performed well [12]. The selection of a rice variety is based on 5 distinctive rice grain characteristics. This approach can be effectively used for the identification of rice varieties from Myanmar using image processing [13]. CNN is used to evaluate a tiny sample of barley grains in terms of quality, but they are not suitable for the industrial sorting of material in bulk [14] by means solely white and black pictures of weed seeds. The bagged classifiers can use a set of 12 features that could derived from white and black images to achieve roughly 98% classification accuracy for n=4. It highlights how ANN strategies fall short of the simpler Bayesian method [15]. The 11 varyingly high-quality spring and winter wheat types images were used for the analysis. Kernel photos were digitalized at a high quality of 400 dpi and 24-bit depths. 11 types of wheat were classified with 100% accuracy using texture feel by bare hands [16]. The 7 rapeseeds were categorized utilizing the 664 scanning images and system offered 90% accuracy [17]. Different color indices and classification techniques to distinguish vegetation from background was used. The discrimination aspect of weed detection is challenging between weeds and crops. Geographical surroundings, visual textures, spectral characteristics, and biological morphology were the features to discriminate [18]. The milled rice grains were categorized into 4 categories using 4 distinct metaheuristic classification algorithms. Color images are used to assign qualitative grades. Classifier performance evaluation revealed that MLP neural network with the best classifier had a 12-5-4 topology and an accuracy 98.72% [19]. Gala and Idared apple farmers' seeds could be distinguished with up to 100% accuracy [20]. A 2-layer BPRH the quicker RCNN-based detection technique was proposed, and it is capable of accurately detecting BPRH. The accuracy and recall rate on the 200 test images were 94.5% and 88.0% respectively [21]. Table 1 summarizes the relevant existing techniques.

Table 1

Comparative Study of Literature

Reference	Grain	Accuracy
Koklu et al., (2020).	Dry Beans	MLP-91%, SVM-93%, DT-87%, KNN-95%.
Arora et al., (2020)	Rice	LR-91%, DT-93%, RF-97%, SVM-95%.
Kurtulmuş et al., (2015).	Rapeseed	SVM-87%, KNN-91%, RF-97.75%.
Zareiforoush et al., (2016)	Milled Rice	DT-94%, SVM-96%, KNN-97%.

3. Methodology

The methodology proposed in this study is aimed at classifying objects in input images, specifically millets samples. The study focused on three millet varieties, namely jowar, bajra and raagi. The schematic block of classification of millets is shown in Figure 1.

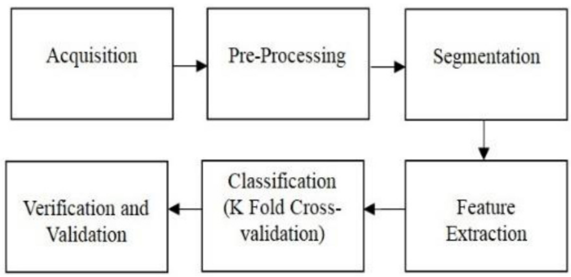
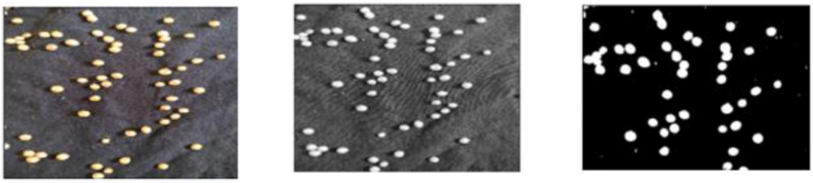


Figure 1

Block Diagram of Image Based Classification of Millets

Image Acquisition One of the initial stages in the process involves obtaining the images. The images are collected from the rear camera with 64MP.The dataset consist of 500 images of each jowar, bajra and raagi. The sample input image is shown in Figure 2.

Image Pre-processing Gray Scaling The next step involves the conversion of RGB color image into gray-scale image. The purpose of this phase is to reduce the complexity of the code and simplify the image. By converting image becomes less complex and easier to process. The gray-scale image is presented in Figure 3.



Input Image Gray-scaled Blurred Image

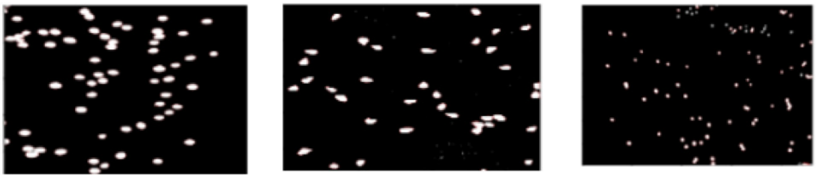
Figure 2

Preprocessing the millet image

Thresholding The popular technique used for image binarization that involves converting a gray-scale image into a binary image with pixels taking on values of either 0 or 1. One of the well-known thresholding methods is Otsu binarization, which automatically calculates the threshold value for a bimodal image based on its histogram . This makes Otsu's binarization an excellent choice for such scenarios. The resulting binary image, as shown in Figure 2, is beneficial for numerous image processing actions like object recognition and segmentation.

Image Filtering After applying binarization techniques such as Otsu's binarization, the resulting binary image may still contain small white noises that can interfere with image analysis tasks. To address this issue, morphological operations are commonly used, specifically the erosion operation followed by dilation while maintaining the size and contour of more substantial items in the picture. The binary image's white regions boundaries are first eroded by morphological opening, which then performs a dilation operation. This process helps to remove small white regions while preserving the overall structure of larger objects. On the other hand, morphological closing is the reverse of opening and is used to close small gaps and fill in small holes inside the visual area. The final output of the preprocessing stage is blurred image, as shown in Figure 2.

*Segmentation S*egmentation was performed on the binary image to identify and isolate individual millet grains. One common technique for segmenting objects in an image is contour detection. It involves identifying the boundaries of objects. Contour detection works by identifying regions of the binary image where the pixel intensity changes abruptly, indicating a change in object boundaries. After contour detection, the resulting contours are drawn on the binary image to highlight the boundaries of individual millet grains. This process involves identifying the coordinates



Jawar Bajra Raagi

Figure 3

Contour Detection

of each contour point and connecting them in a continuous path to form a closed boundary around each grain. Overall, the combination of binarization, morphological operations, and contour detection allows for effective segmentation of millet grains from the original image, which is used for analysis tasks. The output of segmentation is shown in Figure 3.

Feature Extraction The segmented millet grains are used as a source for the feature extraction procedure, which entails obtaining form and texture data. Following that, an ML model that was trained using these attributes was used to categorize fresh image samples into groups like jowar, bajra, and ragi. The form and texture features are later employed to train an ML model, like a decision tree or a random forest, that can categorize fresh millet grain samples according to their features. In conclusion, the combination of structure and texture extraction of features with ML-based classifications offers an efficient method that locating and classifying millet grains and other contaminants in an image. The block diagram of the procedure for identification and classification is shown in Figure 4. In the feature extraction stage, shape feature extraction and texture feature extraction was carried out.

Fusion of Hu Moments and LBP The Hu Moment technique have been used for shape feature extraction. Hu moments are a set of seven-moment invariants calculated from an object's contour. These moments are scale, rotation, and translation invariant, meaning they remain constant for the same object regardless of scale, orientation, or position changes. For millet grain shape extraction, the contour of each grain was first obtained using the contour detection algorithm. Then, the seven Hu moments were calculated from the contour. These moments represent the shape characteristics of the millet grain, such as elongation, symmetry, and compactness, and are used as features for classification. The Texture features are extracted by using Local Binary Pattern. LBP works by dividing the grey-scale image into small regions, called patches, and

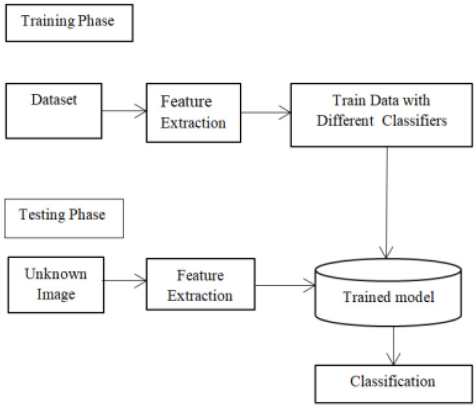


Figure 4

System for classification of Millets

comparing the intensity of each pixel in the patch with the intensity of its surrounding neighbors. Based on this comparison, a binary code is generated for each pixel, which describes the texture of the patch. The performance of object identification systems can be enhanced by combining Hu Moments with LBP. Hu Moments are good in capturing an object's overall shape and structure, whereas LBP excels at capturing local texture information. Combining the two methods results in a feature set that offers a more thorough description of the object, improving recognition precision. Concatenation is used to combine Hu Moments and LBP. The two feature vectors are combined in the proposed method to create a longer feature vector that contains both shape and texture data. Hu Moments and LBP combined can be a potent method for increasing the effectiveness of object recognition systems.

Validation To classify the millet grains into categories namely jowar, bajra and raagi, five machine learning algorithms were applied to the extracted shape and texture features. These algorithms were RF, DT, SVM and KNN. With k = 5, 5 fold cross-validation was used to assess the performance of the classification models. Model was trained and tested 5 times. Different subset served as the test set and the remaining subsets served as the training set. This ensures that the model is trained and tested on all data points in the dataset and helps to avoid overfitting and underfitting. Accuracy, precision, recall, and F1-score criteria were used to assess each model's performance.

4. Results

Machine Learning Algorithms were implemented to analyze the millet class. The performance of classifiers is given in Table 2.

Random Forest Classifier - It improves the performance of single decision trees by using bagging and random feature selection. The process of building multiple models from Random feature selection and bootstrap samples of the training data make up the procedure of selecting a random subset of features for each split in a decision tree. The random forest classifier gave highest mean accuracy of 92%.

Decision Tree builds a predictive models that map observations to conclusions about their target values. The model is constructed as a tree structure, where internal nodes depict the characteristics, and branches represent decision rules that assign a target value to the input. The leaf nodes represent the target values or classes that the algorithm has learned from the data. This classifier provided the mean accuracy of 91%.

Support Vector Machine (SVM) creates a hyperplane or set of hyperplanes. The hyperplane that maximizes the margin between the

Table 2

Results of Classification values in %

Classifier	Accuracy	Precision	Recall	F1-Score
Random Forest	92.00	92.00	92.00	92.00
Decision Tree	91.00	91.00	91.00	91.00
SVM	80.20	80.40	79.70	82.90
KNN	83.60%	83.40	82.80	89.30

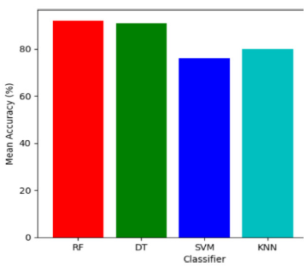


Figure 5

Mean accuracy of classifiers

Jowar Bajra Raagi

Figure 6

Predicted Class of Millet

classes is the aim of SVM. In order to support non-linear classification, SVM uses kernel functions to convert the input data into a higher-dimensional feature space giving the mean accuracy of 80%.

KNN-The KNN is non-parametric classification method . The algorithm uses a distance metric to gauge how closely two data values are similar, and the k neighbors with smallest distances are considered for classification. It gives Mean accuracy of 83%. Figure 5. shows the comparative analysis of classifier performance. The class prediction output of the proposed system is given in Figure 6.

5. Conclusion and Future Scope

The study demonstrated that image processing & machine learning can effectively utilized to distinguish between various millets. The proposed method achieved an accuracy of 91% using random forest algorithm in identifying jowar, bajra, and raagi from images. The method involved several stages, including preprocessing of the images, feature extraction and classification using different machine learning algorithm. The results showed that this approach was successful in accurately identifying millets. The proposed millets identification model can be further developed by adding more types of millets to the dataset and exploring advanced image processing & ML algorithms to improve accuracy of classification. Additionally, the model can be integrated into a mobile app or web application that allows users to identify different types of millets using their smartphone cameras. Furthermore, the potential of millets in addressing food security and malnutrition issues can be explored by conducting further studies on their nutritional properties. Additionally, the model can be deployed in agriculture and food industries for quality control and grading of millets.

References

[1] Wei, W. U., et al. 'Detection and Enumeration of Wheat Grains Based on a Deep Learning Method under Various Scenarios and Scales'. *Journal of Integrative Agriculture,* vol. 19, no. 8, pp. 1998–2008 (2020).

[2] Nayak, S. R., Arora, V., Sinha, U., & Poonia, R. C. A statistical analysis of COVID-19 using Gaussian and probabilistic model. *Journal of Interdisciplinary Mathematics*, 24(1), 19–32 (2021).

[3] Rao, A. Shubha, and K. Mahantesh. 'Impact of Computer Vision Based Secure Image Enrichment Techniques on Image Classification Model'. *Journal of Discrete Mathematical Sciences & Cryptography,* vol. 26, no. 3, Taru Publications, pp. 899–911 (2023).

[4] Wasson, Vikas, and Birampal Kaur. 'Image Quality Assessment: Intelligent Feature Selection Using Soft Computing Techniques'. *Journal of Information & Optimization Sciences,* vol. 44, no. 6, Taru Publications, pp. 1009–1022 (2023).

[5] Jain, S., Kumar, S., Sharma, V. K., & Poonia, R. C. Peregrine preying pattern based differential evolution for robot path planning. *Journal of Interdisciplinary Mathematics*, 23(2), 555–562 (2020).

[6] Altuntas, Yahya, et al. 'Identification of Haploid Maize Seeds Using Gray Level Co-Occurrence Matrix and Machine Learning Techniques'. 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), IEEE (2018).

[7] Koklu, Murat, and Ilker Ali Ozkan. 'Multiclass Classification of Dry Beans Using Computer Vision and Machine Learning Techniques'. *Computers and Electronics in Agriculture*, vol. 174, no. 105507, Elsevier BV, p. 105507 July (2020).

[8] Koklu, Murat, Ilkay Cinar, et al. 'Classification of Rice Varieties with Deep Learning Methods'. *Computers and Electronics in Agriculture,* vol. 187, no. 106285, Elsevier BV, p. 106285 Aug. (2021).

[9] Laabassi, Karim, et al. 'Wheat Varieties Identification Based on a Deep Learning Approach'. J*ournal of the Saudi Society of Agricultural Sciences,* vol. 20, no. 5, Elsevier BV, pp. 281–289 July (2021).

[10] Arora, Biren, et al. 'Rice Grain Classification Using Image Processing & Machine Learning Techniques'. 2020 International Conference on Inventive Computation Technologies (ICICT), IEEE (2020).

[11] Koklu, Murat, Seyma Sarigil, et al. 'The Use of Machine Learning Methods in Classification of Pumpkin Seeds (Cucurbita Pepo L.)'. Genetic Resources and Crop Evolution, vol. 68, no. 7, Springer Science and Business Media LLC, pp. 2713–2726, Oct. (2021).

[12] Lingwal, Surabhi, et al. 'Image-Based Wheat Grain Classification Using Convolutional Neural Network'. Multimedia Tools and Applications, vol. 80, no. 28–29, Springer Science and Business Media LLC, pp. 35441–35465, Nov. (2021).

[13] Lin, Ping, et al. ‘Determination of the Varieties of Rice Kernels Based on Machine Vision and Deep Learning Technology’. 2017 10th International Symposium on Computational Intelligence and Design (ISCID), IEEE (2017).

[14] Poonia, Ramesh C., et al., eds. Smart Farming Technologies for Sustainable Agricultural Development. IGI Global (2018).

[15] Kozłowski, Michał, et al. ‘Varietal Classification of Barley by Convolutional Neural Networks’. *Biosystems Engineering*, vol. 184, Elsevier BV, pp. 155–165, Aug. (2019).

[16] Olgun, Murat, et al. ‘Wheat Grain Classification by Using Dense SIFT Features with SVM Classifier’. *Computers and Electronics in Agriculture,* vol. 122, Elsevier BV, pp. 185–190, Mar. (2016).

[17] Zapotoczny, Piotr. ‘Discrimination of Wheat Grain Varieties Using Image Analysis and Neural Networks. Part I. Single Kernel Texture’. *Journal of Cereal Science,* vol. 54, no. 1, Elsevier BV, pp. 60–68, July (2011).

[18] Kurtulmuş, F., and H. Ünal. ‘Discriminating Rapeseed Varieties Using Computer Vision and Machine Learning’. *Expert Systems with Applications,* vol. 42, no. 4, Elsevier BV, pp. 1880–1891, Mar. (2015).

[19] Wang, Aichen, Wen Zhang, and Xinhua Wei. “A review on weed detection using ground-based machine vision and image processing techniques.” *Computers and electronics in agriculture* 158 : 226-240 (2019).

[20] Zareiforoush, Hemad, et al. ‘Qualitative Classification of Milled Rice Grains Using Computer Vision and Metaheuristic Techniques’. Journal of Food Science and Technology, vol. 53, no. 1, Springer Science and Business Media LLC, pp. 118–131, Jan. (2016).

[21] Ropelewska, Ewa. ‘The Use of Seed Texture Features for Discriminating Different Cultivars of Stored Apples’. *Journal of Stored Products Research*, vol. 88, no. 101668, Elsevier BV, p. 101668, Sept. (2020).