International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 10 | October - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

DETECTION OF CUMIN SEEDS ADULTERATION BASED ON THERMAL IMAGING USING DEEP LEARNING TECHNIQUE

M. HAJERA[1], Dr. M. SANTHI[2], B. DIVYA[3]

[1]*PG Scholar, Department of ECE, Saranathan College of Engineering,* [2]*Professor, Department of ECE, Saranathan College of Engineering,* [3]*Assistant Professor, Department of ECE, Saranathan College of Engineering, Tiruchirappalli-12, Tamil Nadu, India.*

Abstract - Food adulteration refers to the addition of artificial or poor-quality substances to a food product. Since the start of mankind, food adulteration has been a problem that artificial intelligence has successfully detected. In addition to lowering food quality, it also has several adverse health consequences. Two spices that are often used in the food industry are cumin and fennel, although they can be adulterated. Using deep learning, this research established a convolutional neural network (CNN) architecture that can identify between a food product and additional adulterants. This technique accurately detects 95.5% adulteration in cumin and fennel seeds.

Key Words: Food adulteration, thermal imaging, spices, image classification, CNN, inception V3 algorithm.

1. INTRODUCTION

Food product adulteration has adverse effects on consumers' health and the economy. It creates mistrust between customers and vendors. Food adulteration is the practice of adding illegal or unlisted external substances into a food product in order to decrease the quality of the food. Non-permitted colors are the most frequent adulterants. These contaminated food items can also result in gastrointestinal issues, cancer, anemia, brain damage, paralysis, and a host of other medical problems. It is related to food-borne illnesses. Adulteration and food fraud are widespread in nations with weak legal oversight and no sufficient power to oversee the quality of food goods. Therefore, having a simple and inexpensive approach to identify these food frauds will be beneficial. While there are various methods for identifying adulterants in food, none of them can ever be used to properly certify that a product is free of contamination because they depend on the adulterant or method of replacement being known. Standard practices currently rely on manual visual inspection or chemical and physical inspection of the food goods to detect adulteration. e.g., chemo metrics, spectroscopic approaches, conventional optical microscopy, figure-printing techniques, and other screening tools. These processes can be costly and time-consuming, which raises the price of high-quality goods.

To identify food adulteration, this paper proposes an alternative method. This study looks into the possible advantages of employing deep learning algorithms [1] and image processing to identify adulterated spices. It will help make the food product less expensive and considerably cut down on the amount of time needed to find adulteration. My research is to provide a system for anticipating, identifying, and reacting to food adulteration that has legal or commercial motivations. In order to categories the quality control, or lack thereof, of cumin seeds, this research first uncovers the scope of commercially and socially inspired food adulteration before examining the existing techniques used to trace the occurrence of known adulterants.

1.1 Cumin Seeds:

The dried seed of the Cuminum cyminum plant, (as shown in Fig. 1) which is a member of the Apiaceae family, is where cumin seeds are derived. Because of their flavor and aroma, this yellowish-brown substance is utilized as a spice in meals. Cumin seeds have an infinite number of applications. These are also widely utilized in conventional treatments for cholesterol improvement, immune system enhancement, respiratory disease treatment, and aid in digestion. In addition to having antiviral and antibacterial characteristics, cumin seeds are a good source of iron. To manufacture cumin powder, cumin seeds are also crushed. In India, Pakistan, Bangladesh, and Middle Eastern nations, where people typically like spicier food, cumin is most commonly used.

One of the popular spices used in India and other parts of the world is cumin. Around 73% of the cumin consumed worldwide each year is produced in India. India exported cumin seeds worth INR 19.6 billion in 2016–17 [2]. Given the high cost of growing and exporting cumin seeds, buyers and exporters must examine the quality of the product or cumin seeds. If consumable products are adulterated, exporters, buyers, and even consumers could suffer significant financial losses and substantial health hazards. The reputation of a nation on the global trading market can also be damaged by food fraud of any type.

1.2 Fennel Seeds:

The most typical adulterants used to drug cumin seeds are fennel seeds (Foeniculum vulgare) [3]. To deceive the purchasers and cut the price of the seeds, fennel seeds—which are typically coated and dyed with other substances—are combined with cumin seeds [4]. Such adulteration seriously endangers the public's health. Manual visual inspection can be used to quickly find adulteration in cumin seeds. When fennel seeds are mixed with cumin seeds, the fennel seeds will be shorter and lighter in color (as shown in Fig.1). A machine that could distinguish fennel seeds from cumin seeds would be of great use for both consumers and buyers. Given that the visual inspection method is the most effective at identifying adulteration in cumin seeds, we suggest a similar strategy by utilizing an algorithm to visually separate cumin seeds from fennel seeds to help with the more in-depth inspection to identify food fraud.

Fig -1: Digital images of Cumin seeds (left) and their adulterant Fennel seeds (right).

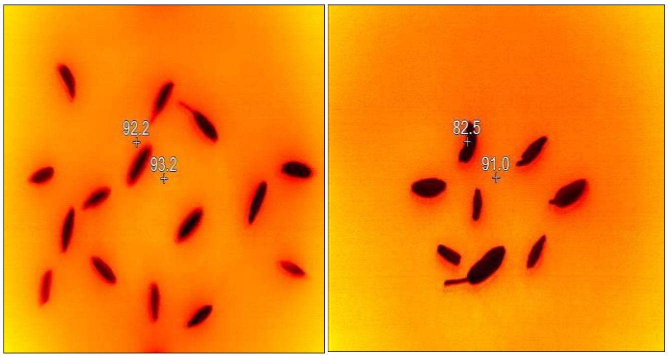

Fig -2: Thermal images of Cumin seeds (left) and their adulterant Fennel seeds (right).

2. LITERATURE REVIEW

Amanda Beatriz Sales de Lima [5] proposes a method for detecting non-targeted and targeted adulteration in black pepper and cumin powder by the addition of starch cassava and maize flour (5%–50%) using NIRs connected to chemo metric models. In contrast to samples of black pepper, the created non-targeted models suggested that chewing was easier to identify in samples of cumin. This model worked well for the two spices of identifying the sort of adulterant. For black pepper and cumin, respectively, a substantial proportion of contaminated samples were found (62% and 79%).

Noor Fatima [6] developed a convolutional neural network system that uses transfer learning to distinguish between a food product and additional adulterants. They used the concept of the Inception algorithm to discover the adulteration in the coffee, cinnamon, and cumin. According to their findings, the newly created model was able to quickly and accurately evaluate different spices, nuts, and beverages.

V.Ponnusamy [8] proposed a solution to the issue of food grain adulteration by using deep learning-based thermal image processing techniques on thermal image samples of different varieties of rice and paddy grains. When it comes to the identification and treatment of impurities, rice and paddy, two of India's basic foods, are of the utmost importance. The proposed methodology achieves the objective of adulteration detection with a 95% accuracy in distinguishing between pure and impure grain images.

Christian Szegedy [16] proposes strategies to scale up networks to make the most of the additional computation through appropriately factorized convolutions and aggressive regularization. They compare their techniques to the state of the art using the ILSVRC 2012 classification challenge validation set and show significant improvements: For single frame evaluation, a network with a computational cost of 5 billion multiply-adds per inference and fewer than 25 million parameters produced errors of 21.2% top-1 and 5.6% top-5. We report a 3.5% top-5 error on the validation set (3.6% error on the test set) and a 17.3% top-1 error using an ensemble of 4 models with multi-crop evaluation.

Abdullah [17] proposes an ML model based on image processing and transfer learning to discriminate between cumin, fennel, and carom. For training and testing purposes, a dataset of 360 photos from each class was constructed. Because they are all members of the same family and have a similar appearance, cumin, fennel, and carom seeds are sometimes mistaken for one another. Seeds of various kinds can be identified and categorized by this method.

3. PROPOSED SYSTEM

Using Fluke thermal imager equipment, thermal images of cumin and fennel samples were captured and kept in an insulation chamber made of wood—a good heat insulator—to prevent the image from being impacted by thermal radiation from the surroundings. Fennel and cumin seeds were kept in both hot and cold conditions for collecting the samples. Camera settings were used to take images in the is2, jpg, and bmp file formats. Cumin and fennel seeds samples of 300 thermal images were captured and gathered. For training 200 images were given. For testing 100 images were given and 100 images were used for validation. In the spices industry, fennel and cumin seeds are frequently used, that are contaminated with substances like sand, sawdust, or starch. In this paper, fennel and cumin adulteration can be found using a Convolutional Neural Network (CNN) method. The deep learning algorithm known as CNN is frequently applied for image classification.

Finally, 300 images representing the three classes of cumin, fennel, and mixed (adulterant) seeds were collected. The first step is to reduce all the images to 240×240 in the pre-processing phase. To boost several photos, image enhancement was performed. Things like flipping and rotating the existing image make it possible to generate training data that is more diverse and can improve the model's ability to generalize while being trained. The two primary parts of an average image classification task are feature extraction from the images and classification [13].

Utilizing Inception V3 [16], the model extracted features. By altering the Inception designs from past versions, Inception v3's main objective is to use less computational power. Through the incorporation of an output layer for classification that is flattened and dense after the pre-trained architecture. After that, a few layers were added and trained using the features that were extracted from the image. Followed by adding a flattened layer, which turns the output of the layer preceding it into a vector. The next layer is dense, consisting of 1024 neurons, and it has rectified linear units (ReLU) that serve as activation units. The last step is to design an output layer with a softmax or sigmoid function, based on the number of classes in the classification [18]. These interpret the result as a forecast between the categories. Each image received a scalar value after being passed across the network. Because of the pre-trained weight, the model produced the results in 8 epochs.

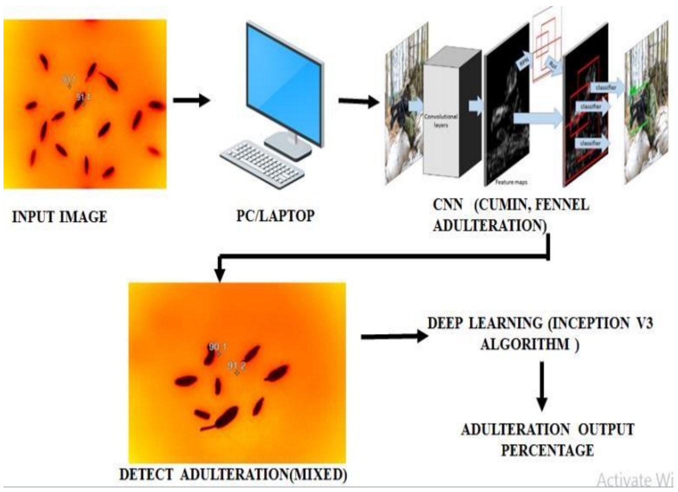

Fig -3: Block diagram

3a. Data Gathering: The initial phase is gathering a sizable dataset of thermal pictures of fennel and cumin seeds (as shown in Fig. 3) both from authentic and tampered samples. Various lighting conditions, angles, and seed sizes should be present in the dataset to ensure diversity.

3b. Data Preprocessing: Thermal images must be preprocessed after the dataset is gathered to get rid of any noise or artifacts. By scaling the images to a fixed size, making them gray scale, and using noise-reduction filters, this can be accomplished.

3c. Feature Extraction: Features are taken out of the pre-processed thermal input photos in this step. Automatic feature extraction can be done with Convolutional Neural Networks (CNN). Convolutional layers that are followed by pooling layers make up the CNN architecture, which can learn from the input image properties like edges, textures, and patterns.

3d. Convolutional Neural Network (CNN): To extract and learn features from the input images, design CNN architecture with numerous convolutional layers, pooling layers, and fully connected layers.

3e. Training model: Training a deep learning model with the obtained features comes next after feature extraction. Using supervised learning, the model can be instructed to distinguish between original and fake fennel and cumin seeds using the features that were taken from the input thermal images.

3f. Validation and Testing: To determine the trained model's performance, it must be put to the test on a different collection of images. Users can also upload thermal images of cumin and fennel seeds to evaluate the validity of adulteration.

4. CONVOLUTIONAL NEURAL NETWORK [CNN]

4a. Input Layer: The network's input layer is where the network receives the preprocessed thermal image of the seeds. The input layer must be the same size and shape as the previously processed image (as shown in Fig. 4).

4b. Convolutional Layers: The brain of the CNN algorithm (as shown in Fig. 5) is the Convolutional Layers. These layers are used to extract the most crucial details from the source image. To do this, a set of filters that recognize patterns like edges, corners, and forms are applied to the input thermal image.

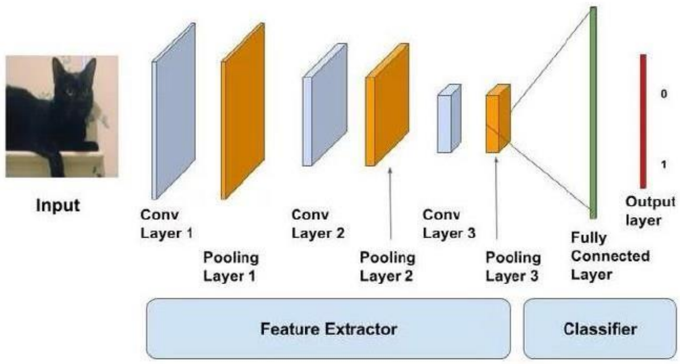

Fig -4: Convolutional layers

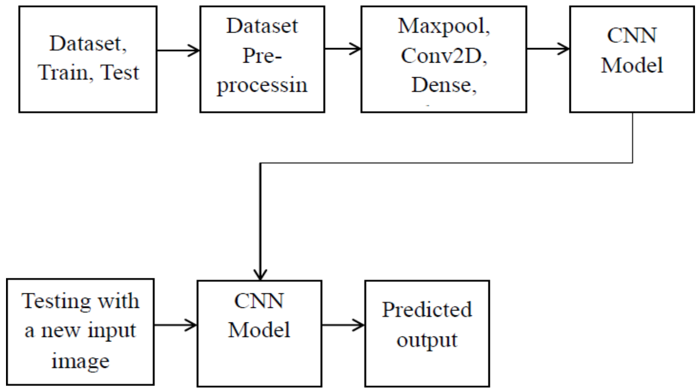

Fig -5: Architecture of CNN

4c. ReLU Layers: The output of the Convolutional Layers is subjected to a non-linear activation function called the Rectified Linear Unit (ReLU) Layer. The ReLU Layer contributes to the network's introduction of non-linearity, which is crucial for detecting intricate patterns in the input data.

4d. Pooling Layers: The output from the ReLU Layers is reduced in dimension by the employment of the Pooling Layers. This is accomplished by taking the highest or average value of a tiny portion of the output. Pooling Layers assist in lowering the amount of parameters in the network, making it less susceptible to over fitting.

4e. Flatten Layer: The output from the Pooling Layers is transformed into a one-dimensional vector using the Flatten Layer. This is required since most classifiers require a one-dimensional input, but the output from the Pooling Layers is still in the form of a 2D matrix.

4f. Fully Connected Layers: Based on the features gleaned from the input image, the Fully Connected Layers are used to generate the final predictions. The output from the preceding layer is flattened by the Fully Connected Layers, who then add a set of weights to it. These weights are learned by the network during its training phase.

4g. Output Layer: The output layer, the last layer in the network, is responsible for producing the final predictions. The number of classes in the problem determines how many nodes there are in the output layer. For instance, there would be two nodes in the Output Layer, one for each class, if we were looking for adulteration in cumin and fennel seeds.

5. INCEPTION-V3 ARCHITECTURE

A convolutional neural network with 48 layers deep is called Inception-v3. The ImageNet database contains a pre-trained version of the network that has been trained on more than a million pictures. The pre-trained network can categorize photos into 1000 object categories, including several animals, a keyboard, a mouse, and a pencil. The network has therefore acquired rich feature representations for a variety of images. The size of the network's picture input is 299 by 299 pixels. For further MATLAB® pre-trained networks. Convolutional neural network design from the Inception family, Inception-v3, provides several enhancements, employing Label Smoothing among them. I use categorize to classify new images using the Inception-v3 model. The inception V3 architecture (shown in Fig. 6) has 48 layers in total, which is slightly higher than the inception V1 and V2 models. But this model's effectiveness is truly astounding.

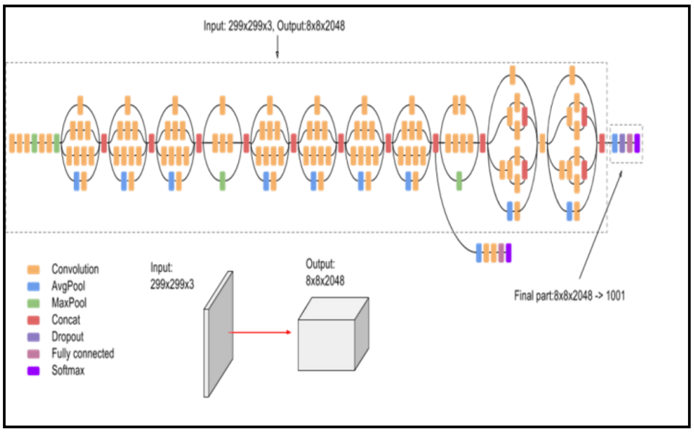

Fig -6: Inception V3 architecture

6. HARDWARE AND SOFTWARE SETUP

6.1: Hardware Setup:

The hardware part of the system consists of the Thermal Image Capture and the insulated chamber inside which the food items that are to be validated are placed.

Fig -7: Hardware Setup (Camera is set upon the insulated chamber)

6.1.1 : The Insulation Chamber:

The chamber is made of wood, (shown in Fig. 7) which is a good insulator of heat and does not allow the image to be influenced by thermal radiation from the surroundings. Its dimensions are 30 cm x 30 cm x 25 cm in length, breadth, and height respectively. The inner layer is further padded with thermocol to prevent the heat from within the chamber from escaping into the environment. It is then coated with a layer of black paint so that the image captured can be viewed in high quality due to the clear background the black color offers. This black layer of paint also acts as a good thermal absorber, which gives the images an even better quality.

6.1.2 : Thermal Camera:

Many different things can be done with thermal imaging cameras, (as shown in Fig. 8) often known as heat sensor cameras or thermal imaging guns. To get varied temperature distributions of thermal imaging for food matrices, chemical, or biological materials, it is necessary to take into account the fact that the emissivity of the substance is temperature-dependent. A portable camera equipped with an image processing system typically provided by the manufacturer that can record both RGB and thermal pictures serves as the basis of the thermography equipment. Typically, thermal imaging cameras produce images with a resolution of between 320 x 240 pixels and 1280 x 960 pixels, assess temperature with great accuracy (up to 1200 °C), and have a spectral range in the far-infrared spectrum between 7.5 μm and 13 μm.

Fig -8: Images of Thermal Camera

6.1.3 : Hardware description:-

- Laptop - MSI RAIDER GE77.
- Insulation chamber.
- Fluke TiX580.

6.2: Software setup:

The software part of the project consists of the SmartView® Software and MATLAB libraries to implement the CNN algorithm. The images can be viewed, analyzed, and edited in the SmartView® Software to produce a large dataset from just a few captured images. This dataset is then divided into Training, Testing, and Validation data for the Neural Network to be analyzed.

6.2.1 : SmartView® Software:

SmartView (shown in Fig. 9) is a powerful, yet easy-to-use, analysis and reporting software provided for exclusive use in Fluke Thermal Imagers. This software is a modular suite of tools that views, optimizes, and analyses infrared (IR) images and visible light control images. It also generates fully customizable, detailed, and professional-looking reports containing important image data in a few easy steps.

The software is easy to use for maintenance and building professionals yet delivers the performance specialized thermographs require for advanced analysis. SmartView, together with the thermal imager, helps in transferring the thermo graphic images to a computer and efficiently managing them.

Fig -9: SmartView® Software

6.2.2 : Software description:-

- Smart View® Software.
- MATLAB (R2021a), 64-bit (win64)

  Libraries files in MATLAB:
  - Image processing toolbox.
  - Deep learning Toolbox for inception V3 architecture.
  - Computer vision toolbox.

7. RESULT AND DISCUSSION

Regarding cumin seeds, we have achieved an accuracy rate of 95.5%. In Fig. 10 and in Fig.11, the accuracy and losses have been displayed. The accuracy levels depend on the quantity of samples offered. The final classification output is obtained (as shown in Fig.12).

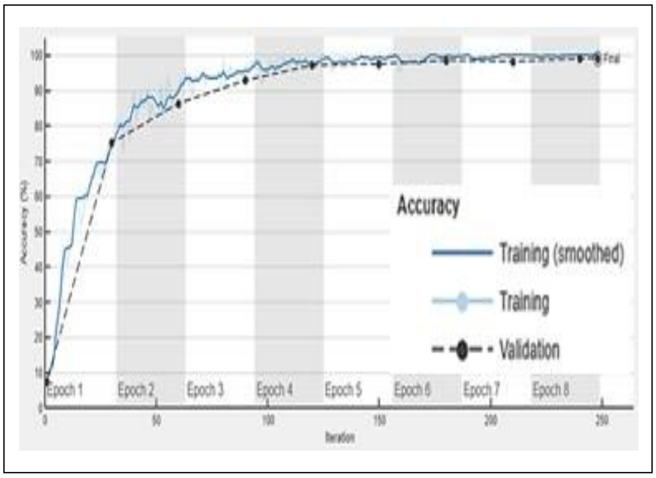

Fig -10: Accuracy plots of cumin seeds

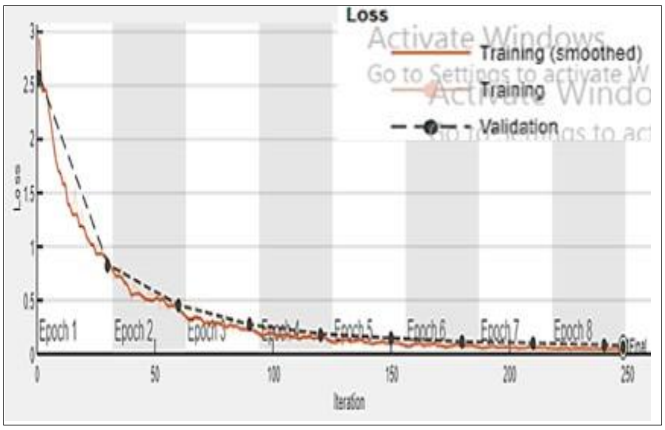

Fig -11: Loss plots of cumin seeds

7a. Sensitivity:-

The model's sensitivity measures how well it can recognize instances of the positive class.

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

7b. Specificity:-

The model's specificity is a metric for how well it can recognize instances of the negative class.

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

7c. Accuracy: -

The model's performance across all classes is described by its accuracy metric. When every class is equally important, it is useful. It is determined as the ratio of the number of accurate predictions to all predictions.

$$Accuracy = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}}$$

7d. Precision:-

The ratio of correctly identified Positive samples to all Positive samples (both correctly and wrongly classified) is used to compute the precision. The precision measures how accurately a sample is classified as positive by the model.

$$Precision = \frac{True_{positive}}{True_{positive} + False_{positive}}$$

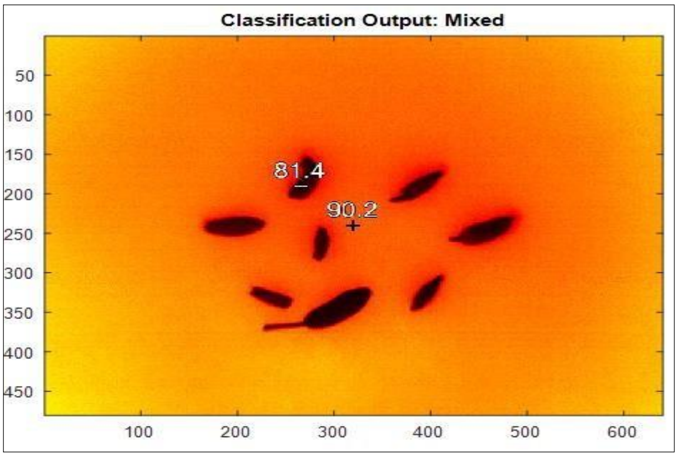

Fig -12: Classification Output (Adulterant seeds)

Sensitivity, specificity, accuracy, and precision values of the examined picture are determined and obtained (as shown in Fig. 13).

Selected File Name: IR_00653.JPG

Predicted Label: Mixed

Sensitivity = 0.111237

Specificity = 0.0147688

Accuracy = 0.955346

Precision = 0.210526

Fig -13: Accuracy and precision values of tested image

In the modern era, it is common practice for vendors and suppliers of foods and spices to adulterate them with hazardous imitators to increase their profits at the expense of endangering the health of their customers. Food authenticity is therefore a serious problem about food fraud. Such occurrences have increased as a result of easy access to food ingredients and the industry's push to produce food products at lower costs. However, the development of numerous techniques for identifying adulterants in food, including physical, biological, chemical, immunological, and molecular approaches, has been facilitated by awareness of food standards and regulations. For the detection of biological food adulterants, molecular methods are favored, whereas physical and biochemical methods are favored for the detection of other food contaminants. A technique that ordinary people can use to detect adulteration without the aid of lab equipment or scientific expertise is required. This paper offers a unique, non-destructive, and effective method for distinguishing authentic cumin seeds from their corresponding adulterants based on artificial neural networks.

The advantages of employing this technology over the currently used screening methods for identifying and quantifying adulterants in these spices include the lack of a need for skilled analysts and testing equipment for quality control, as well as the cost-effectiveness of implementation. Since it is a non-destructive method, it might be used on any product sample, which is subsequently combined with the remaining quantity of that product because samples are not harmed or contaminated by chemical reagents. Because these models might be implemented through mobile applications with an intuitive user interface, it will be possible for traders, merchants, and even normal customers to carry out the authenticity check of these products, which would help in reducing the increase of food adulteration.

8. CONCLUSION

To summarize, the proposed system uses a CNN algorithm and achieves good results in identifying adulteration in fennel and cumin samples. The food industry can be made safer and more dependable by using artificial intelligence techniques like CNN to help in the identification of adulteration in food products. To spot adulteration in cumin and fennel seeds, CNN and inception V3 algorithms can be combined. These algorithms can deliver precise and trustworthy findings for identifying adulteration and can support ensuring the product's quality and safety. This research demonstrates how determining the amount of adulterants in cumin seeds and fennel seeds has become significantly simpler by employing an innovative approach based on Convolutional Neural Networks [CNN] and deep learning.

9. FUTURE SCOPE

Considering our future scope, we would like to extend our work by cascading two or more architectures, which would require much more collection of data samples and more complex algorithms using deep learning for good accurate prediction. More robust and unconventional Feature-based distant domain transfer learning [19] can be leveraged in the future to make systems more efficient.

ACKNOWLEDGEMENT

The authors wish to acknowledge All India Council for Technical Education (AICTE), for funding this project under Research Promotion Scheme (RPS) [File No. 8-70/FDC/RPS/POLICY-1/2021-22].

REFERENCES

1. E. Sun, "Small-scale image recognition based on Cascaded Convolutional Neural Network", 2021 IEEE 5th Advanced Information Technology Electronic and Automation Control Conference (IAEAC), vol. 5, pp. 2737-2741, 2021.

2. D. V. Kumar, "Cumin: Supply Chain Constraints and Prospects", Rural Pulse, 2017.

3. P. Galvin-King, S. A. Haughey and C. T. Elliott, "Herb and spice fraud; the drivers challenges and detection", Food Control, vol. 88, pp. 85-97, 2018.

4. P. John, "Adulterated cumin seeds seized from 3 Unjha factories", Times of India, October 2012, [online]Available:https://timesofindia.indiatimes.com/city/ahmedabad/Adulterated-cumin-seedsseized-from-3-Unjhafactories/articleshow/16871715.cms.

5. Amanda Beatriz Sales de Lima, Acsa Santos Batista, Josane Cardim de Jesus, Jaqueline de Jesus Silva, Antônia Cardoso Mendes de Araújo, Leandro Soares Santos, –Fast quantitative detection of black pepper and cumin adulterations by near-infrared spectroscopy and multivariate modeling‖, Food Control, Volume 10, 2020, 106802, https://doi.org/10.1016/j.foodcont.2019.106802.

6. N. Fatima, Q. M. Areeb, M. M. Khan and I. M. Khan, "Tracing Adulteration in Cumin, Cinnamon, and Coffee using Transfer Learning," *2021 International Conference on Data Analytics for Business and Industry (ICDABI)*, Sakheer, Bahrain, 2021, pp. 562-566, doi: 10.1109/ICDABI53623.2021.9655951.

7. K. Boonyuen, P. Kaewprapha, U. Weesakul, and P. Srivihok, ‗Convolutional Neural Network Inception-v3: A Machine Learning Approach for Leveling Short-Range Rainfall Forecast Model from Satellite Image', in *Advances in Swarm Intelligence*, Y. Tan, Y. Shi, and B.

Niu, Eds., Cham: Springer International Publishing, 2019, pp. 105–115.

8. V. Ponnusamy, P. Anand, and V. Bhatt, ‗Classification of Adulterated Food Grain Thermal Images Using Convolutional Neural Networks', in *Advanced Communication and Intelligent Systems*, R. N. Shaw, M. Paprzycki, and A. Ghosh, Eds., in Communications in Computer and Information Science. Cham: Springer Nature Switzerland, 2023, pp. 475–480. Doi: 10.1007/978-3-031-25088-0_42.

9. Merlne Magrina and M. Santhi, ―Ancient Tamil Character Recognition from Epigraphical Inscriptions using Image Processing Techniques‖, Journal of Telecommunication Study, Vol. 4, Issue. 2, 2019.

10. E. Hong, S. Y. Lee and J. Y. Jeong, "Modern analytical methods for the detection of food fraud and adulteration by food category", Journal of the Science of Food and Agriculture, vol. 97, no. 12, pp. 3877-3896, 2017.

11. P. Kharel, Spice Adulteration - White paper, 2004, [online]Available:https://www.scribd.com/doc/271820633 /Spice-Adulteration.

12. C. Pasquini, "Near Infrared Spectroscopy: Fundamentals Practical Aspects and Analytical Applications", Journal of the Brazilian chemical society, vol. 14, pp. 198-219, 2003.

13. N. Fatima, "AI in Photography: Scrutinizing Implementation of Super-Resolution Techniques in Photo-Editors", 2020 35th International Conference on Image and Vision Computing New Zealand (IVCNZ), 2020.

14. C. Wang *et al*., "Pulmonary Image Classification Based on Inception-v3 Transfer Learning Model," in *IEEE Access*, vol. 7, pp. 146533-146541, 2019.

15. B. Divya, M. Santhi, ―Modified Convolutional Neural Network Based Automatic Detection And Classification Of Insects In Agricultural Fields‖, Journal of Green Engineering (Jge), pp. 2766-2783, Vol. 11, Issue. 3 mar 2021.

16. C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision", In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2818-2826, 2016.

17. Abdullah Ajaz Siddiqui, Shahab Saquib Sohail, Qazi Areeb, Wathiq Mansoor, Md Tabrez Nafis, "Classification of Cumin, Fennel and Carom Using Transfer Learning", 2022 5th International Conference on Signal Processing and Information Security (ICSPIS), pp.46-49, 2022.

18. N. Fatima, Q. M. Areeb, I. M. Khan and M. M. Khan, "Siamese Network-Based Computer Vision Approach to Detect Papaya Seed Adulteration in Black Peppercorns", Journal of Food Processing and Preservation, 2021.

19. S. Niu, Y. Hu, J. Wang, Y. Liu and H. Song, "Feature-based Distant Domain Transfer Learning", 2020 IEEE International Conference on Big Data (Big Data), pp. 5164-5171, 2020.

20. S. Hariprasath and M. Santhi, ―Efficient Implementation of Multi Modal Biometric Pattern Recognition using Supervised Neural Network‖, International Journal of Advanced Technology in Engineering and Sciences, pp. 323-336, Vol. 5, Issue. 2, Feb 2017, ISSN: 2348-7550.

21. A. Krizhevsky, I. Sutskever, and G. E. Hinton, ``Imagenet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NIPS)*, Stateline, NV, USA, 2012, pp. 1097_1105146540 vol.7, 2019.

22. X. Jiang, Y. Pang, M. Sun, and X. Li, ``Cascaded subpatch networks for effective CNNs," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 7, pp. 2684_2694, Jul. 2018.

23. K. Yanai, and Y. Kawano, ―Food Image Recognition using Deep Convolutional Network with Pre-Training and Fine-Tuning‖, *Proceedings of IEEE International Conference on Multimedia and Expo Workshops*, pp. 1-6, 2015.

24. K. Simonyan and A. Zisserman, ``Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, San Diego, CA, USA, Apr. 2015, pp. 1_14.

25. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan,V. A. Vanhoucke, and V. Rabinovich, ``Going deeper with convolutions,"in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Boston, MA, USA, Jun. 2015, pp. 1_9.

26. J. Feng and X. Tang, ‗Office Garbage Intelligent Classification Based on Inception-v3 Transfer Learning Model', *J. Phys. Conf. Ser.*, vol. 1487, no. 1, p. 012008, Mar. 2020, doi: 10.1088/1742-6596/1487/1/012008.