A New Approach for Classification of Spices to make Special Herbal Tea using Caralluma Fimbriata

Prajwal Kumar. P[1], Shivakumara Palaiahnakote[2], Basavanna M[1], Ravikumar Patil H. S[3] and Vyshali V. M[3]

[1]Department of Studies in Computer Science, Davangere University, Davangere, Karnataka, India. prajwalkumarprof@gmail.com, basavanna_m@yahoo.com

[2]School of Science, Engineering & Environment, University of Salford, UK, s.palaiahnakote@salford.ac.uk

[3]Department of Studies in Food Technology, Davangere University, Davangere, Karnataka, India. patil_varuni@rediffmail.com

[4]B.M.S College for Women, Basavanagudi, Bengaluru, vyshali@bmscw.edu.in

Abstract

Classification of multiple types of spice images is automatically challenging due to conflict between the texture patterns of spice images. This work aims to develop an automatic system for classifying different types of spice images so that the system can choose an appropriate spice to make herbal tea using Caralluma fimbriate. This work considers the following seven spices, namely, cinnamon, citrus peel, clove, ginger, jeera, kokum, mint, and Caralluma fimbriata as one more class for classification. Most of the existing systems need human intervention to choose different spices to make Caralluma fimbriata tea. It is observed that the pattern of different spice images represents different textures. This observation motivated us to extract features based on multi-Sobel kernels. To reduce the number of computations, the proposed work introduces a novel idea of corner detection based on Gaussian distribution. For each corner, the method performed is multi-Sobel kernels for extracting features. The features are fed to convolutional neural network layers for the classification of multiple spice images. The results of our dataset and comparative study with the state-of-the-art methods show that the proposed model is superior to existing methods in terms of classification rate.

Keywords: Corner Detection, Ssoble kernels, Convolutional neural network, Classification of spice images.

1. Introduction

The trend of using herbal cures as an alternative to modern medicine is increasing day by day. Many people in the world are slowly convinced of the benefits of herbalism for several ailments, diseases, and disorders. One such popular drink is consuming herbal tea for curing several ailments such as cold, cough, headache, stress, and other related disorders. Therefore, this work focuses on making herbal tea using Caralluma Fimbriata and adding spices to flavor (Shinwari et al.,2011). Peppermint, clove, cinnamon, kokum, ginger, citrus powder, and jeera are the spices considered in this work for making herbal tea with Caralluma Fimbriata. The use of Caralluma Fimbriata for different medicines has a long history of treating various conditions including diabetes, rheumatism, paralysis, leprosy, and inflammation. As it is nutritionally dense and abundant in phytochemicals, Caralluma Fimbriata has been consumed as a vegetable for centuries. It is eaten raw either with spices or preserved in chutneys and pickles (Anwar. R et al., 2022, Mao et al., 2019, Srinivasan, 2018, McKay et al., 2006, Park et al.,2011, Lim et al., 2021)). However, the key problem is that there is no automatic system to choose spices and Caraluma fimbriata to make tea. At present, the process requires human intervention to choose spices to make herbal tea. This is not feasible in terms of scaling, production, taste, and testing in different proportionality.

Fig .1. Sample Images of Eight Classes

Therefore, to develop an automatic system to make herbal tea, there is a need for classifying the above-mentioned seven spices and Caralluma Fimbriata. Thus, we propose a new classification model for classifying eight classes including the Caralluma Fimbriata class. There are methods developed in the past for the classification of images, scene images, medical images, leaf images, etc. in literature. We can also see powerful deep-learning models for classification (Rahaman et al. 2022, Weijie et al. 2021, Srinitya et al. 2023, Socher et al. 2013). However, it is noted that the performance of the models depends on the number of samples. Generalization may not be optimal with a smaller number of samples. In addition, the variation in texture pattern is unpredictable for all the classes. In this situation, it is not so easy to collect many samples that can represent the possible cases. These two observations make us propose the combination of feature extraction and convolutional neural network for the classification of seven spice images and the Caralluma Fimbriata class.

At the same time, it is noted from existing classification methods including deep learning models that none of the methods consider the above seven spice images for classification. Therefore, it is a new problem and hence this work is the first of its kind. However, when we look at the sample images shown in Fig. 1, although the pattern looks like the textures are distinct from each other, variations in the same texture pattern make the problem more complex and challenging. To reduce the complexity of the problem, our idea is to detect corners and then use the local area of corners to extract texture features for classification.

To achieve this, we propose a new corner detection method that uses spatial distance values and Gaussian distribution over distance values. The Gaussian distribution over spatial distance values indeed provides important cues for curvature or curve on the line. This cue is used for corner detection in this work. For each corner, we propose multi-Soble kernels for extracting local texture around the corner, resulting in a feature matrix. The feature matrix is fed to the convolutional neural network for classification. The reason for using multi-Sobel kernels to extract local texture features is that gradient information is invariant to small variations in the colour values and changes in background and foreground colours (Mallikarjuna et al. 2022, Xun Sun et al.2023). Since the gradient features provide distinct values for each class, we explore simple CNN for classification rather than a heavy deep-learning model. Overall, it is noted that the proposed work explores a combination of pattern recognition concepts (Gaussian distribution for corner detection), image processing concepts (Multiple Sobel kernels for feature extraction) and artificial intelligence concepts (Adapting convolutional neural network for corner detection, feature extraction and classification). The key contributions are as follows.

- Introducing a new problem and addressing complex problems with simple solutions
- Proposing spatial distance values between the centre of the local region and its boundary points, and Gaussian distribution for corner detection is new
- Extracting multi-Sobel kernels for texture feature extraction from the local region around the corner is a novel idea for classifying seven spice images and the Caralluma Fimbriata class

The paper is summarized as follows. The methods related to the classification of general images are discussed in section 2. The steps of corner detection, texture feature extraction, and classification using convolutional neural networks are presented in section 3. Section 4 discusses the experimental results and validation of the proposed method. The findings are summarized in section 5.

2. Related Work

Literature on classification can be divided broadly into the methods of general image classification, the methods of food image classification, and the methods of spice image classification.

2.1. Scene Image Classification

Maryam A.et al. (2023), proposed the concept on sensitive scene classification using spatiotemporal edges. Scene classification is achieved by segmenting foreground objects and background frame differences. The random forest classifier is used for the classification of video. However, the scope of the method is limited to video and datasets but not spice images.

Ashwath et al. (2023), proposed a method with three branches such as learning, selection, and fusion using TS-CNN architecture for medical image classification. However, the main weakness of the method is that it is sensitive to distortion and noise. Jie Du et al. (2023), proposed a method for medical image classification using DCNN parameters. The approach uses Region-similar Aware (RSA) and Feature-similar Aware (FCA) methods for classification. Yan-e Hou et al. (2023) extracted the deep-level global features using CNN for remote sensing scene classification. In addition, this method generates contextual spatial channel attention features to improve the performance of the classification method. Ayan Mukherji et al. (2023) proposed methods for biomedical diagnosis. This approach uses different clustering for medical image classification. This aims to improve healthcare choices by analyzing extensive medical data.

Romario Sameh, (2023) demonstrated the methods for the classification of cancer types. Efficient Net is used to achieve multi-class classification in cases of brain tumour, breast cancer mammography, chest cancer, and skin cancer. Yuqun Yang et al. (2023) developed a method for scene classification using a semantic aware graph network. Dense Feature Pyramid Network (DFPN), Adaptive Semantic Analysis Module (ASAM), and Scene Decision Module (SDM) are the key components of the method to achieve the best results.

Sasikumar et al. (2023) proposed a method for medical image classification based on Double U-net and Poly U-net, VGG and Inception-V3. This approach explores segmentation for improving the classification performance. Zhu et al. (2023) developed a model for the classification of medical images through EEG signals. This approach uses a graph neural network for embedding EEG signals and a multi-scale attention mechanism for the classification of images. Potadar et al. (2023) focused on multi-class brain tumour classification based on RN-based deep convolutional neural network. Before classification, this approach segments the region using an Adaptive Canny Mayfly Algorithm (ACMA) model. Panda et al. (2023) used a Grey-Level Co-occurrence Matrix (GLCM) and a Grey-Level Run-Length Matrix (GLRM) for crop classification. Singh et al. (2024) proposed a deep learning model for the classification of multi-type images which includes ten different visual recognition tasks.

In summary, most of the methods focus on scene images and medical images for classification but not spice images. Therefore, the methods may not be effective for spice image classification.

2.2. Food Image Classification

Anitha et al. (2023) presented a method for recipe recommendation. The main objective of the method is food image classification. To achieve this, the approach used is a convolutional neural network. Elena Denny Cherpanath et al. (2024) proposed a method for food image classification using R-CNN methods. Their main goal is to predict the number of calories present in the food by the Faster and Mask R-CNN method. Pranav Kathar et al. (2024) developed a method for food classification using Vision Transformers (ViTs). The transformer has been used to extract visual features for classification. It is shown that the hierarchical classifiers are better than traditional classifiers with larger datasets. Fotios S. et al. (2024) introduced the concept of image classification to analyze dietary of Mediterranean foods. The deep-learning approach has been explored for classification particularly, the EfficentNetB2 method used for classification.

Lihua Luo. (2023) introduced a new deep-learning model for food image recognition. This idea uses the YOLOv5 CNN structure for successful classification. Natesan et al. (2023) proposed a two-class classification for classifying food items in terms of healthy and unhealthy using deep learning. Ramkumar et al. (2023) used a layer-based method (DNN) for calorie prediction within food items. The key objective is to classify food class and predict its calories. In a nutshell, through the review of the above methods, one can assert that the method works well for particular types of datasets and images but not spice images, where one can expect large variations within the images and classes.

2.3. Spice Image Classification

Muhammad Insan Al-Amin, et al. (2022) proposed a method for spice image classification. The approach uses conventional techniques called support vector machines for classification. This work considers five classes of spices for classification. This conventional approach is not effective for complex spice images. Jana et al. (2022) presented a method for the classification of Indian spices using deep-learning model. The method uses grading features for categorization. The method is not robust for poor-quality images because the colour features are sensitive to distortion and degradation.

Kaharuddin et al. (2019) developed a conventional method for the classification of spice types using a traditional k-nearest neighbour algorithm. This approach uses texture features for multi-class classification. However, the method is computationally expensive because k-means clustering involves several iterations.

Chuang Niu, (2022) proposed a method for classification using clustering. The method is effective for small datasets and particular datasets. Ira Safira, et al. (2023) explored naive Bayes methods for categorizing different spices. Muhlis Tahir et al. (2023) proposed a method for the classification of spices and herbs namely, variants in Madura. However, the key objective of the method is not the classification of spices which is the focus of the present work. Maruf Hasan Talukder et al. (2022) proposed a deep-learning method for spice recognition. However, the performance of the method depends on human intervention. In summary, though there are methods for classifying spice images, those methods focus on different spices and the concepts used for classification are different from the concepts used in the present work.

Overall, we can see elegant classification methods for general scenes, medical, food, and spice images, which explore deep learning models to achieve better results. However, the spices considered in our work are different and the steps used for classification are different from the state-of-the-art methods. Therefore, the classification of seven species and one more class Caralluma Fimbriata is still considered a new challenge. Thus, this study aims to develop a new model for the classification of different spices so that the system can choose an appropriate spice to make herbal tea.

3. Proposed Methodology

In this work, we consider seven classes of spices, namely, mint, clove, cinnamon, kokum, ginger, citrus powder, jeera, and Caralluma fimbriata as one more class, resulting in eight classes. Therefore, the objective is to classify eight classes. As mentioned in the previous section, the problem is complex. This is due to variations in the texture pattern of intra-classes. To reduce the complexity of the problem, we propose a method for corner detection using Canny edge images of the input images. We believe that corners and their neighbour information provide important features for discriminating classes of different spices. In addition, corner detection removes most of the background information and hence complexity of the classification problem is reduced. To extract the local texture of the input images, the proposed work introduces multi-Sobel kernels to perform over the image by feeding corners as inputs. The extracted features are fed to the convolutional neural network layer for classification. A block diagram of the proposed work is shown in Fig. 2.

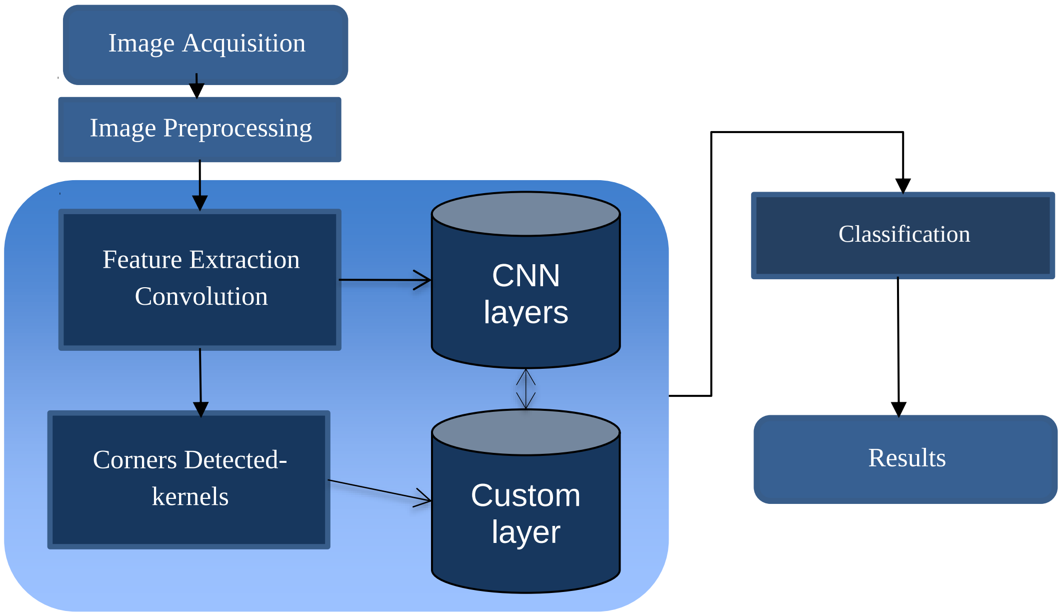

Fig.2 Block Diagram of Proposed method

3.1. Feature Extraction for Corner Detection

For input of each class, the proposed method obtains a Canny edge image. Each edge in the Canny edge image is considered a line to find starting and ending points by traversing the boundary of the edges. The proposed method divides the whole line into 10×10 parts. The value of 10 is determined empirically based on knowledge of the curvature of the line. For each part of the line segment, the method calculates the centroid and estimates the distance between the centroid and boundary points of the line as shown in Fig. 3, where it can be seen, that the lines between the centre and boundary points represent the distance between the centroid and points of the line. This results in distance values for each part of the line segment. To determine corner points using distance values, the proposed method uses Gaussian operation over distance values in a novel way.

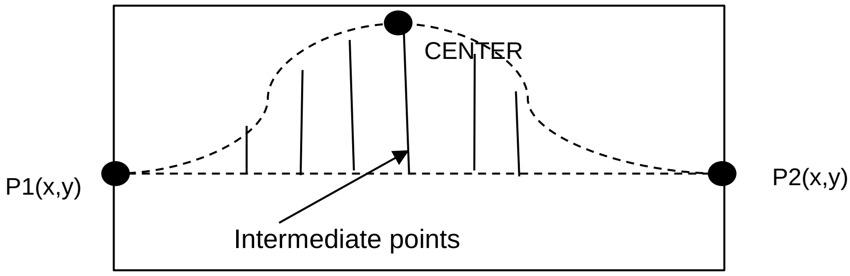

Fig.3. Corner detection using Gaussian distribution.

When the distance values satisfy the Gaussian distribution, the pixel that gives the highest distance is considered as a corner point. Qualitative results of corner detection can be seen in Fig. 4, where one can see successful corner detection for sample images of all eight classes. In Fig. 4, it is seen that the number of corner detections varies from one image to another. This shows that corner detection helps us to extract distinct feature extraction for classification.

Fig.4. Sample results of corner detection

3.2. Gradient Kernels for Feature Extraction from Corners

In this work, unlike performing multi-Sobel kernels as shown in Fig. 5, where we can see kernels of different directions and values, over an image in a spatial domain, the proposed work considers multi-Sobel kernels as convolutional masks to operate. This is a new idea of performing Soble masks as convolutional neural network layers. The following steps are used to design CNN for implementing multi-Sobel kernels for feature extraction. The 3×3 Sobel filter is represented as a 3×3 matrix of weights, and it is applied through convolution with the input image as shown in Fig. 6. For a 3×3 Sobel kernel, the weights are typically chosen such that they follow the Gaussian distribution centered around the central element of the kernel. The effectiveness of multi-Sobel kernel operation through CNN layers is illustrated in Fig. 6, where we can see feature maps are obtained by performing CNN layers on corners of the input images. In this way, the proposed method extracts distinct features for classification.

HORIZONTAL-VERTICAL

$$\begin{bmatrix} 1, 2, 1 \\ 0, 0, 0 \\ -1,-2,-1 \end{bmatrix} \begin{bmatrix} 1, 0, -1 \\ 2, 0, -2 \\ 1, 0,-1 \end{bmatrix}$$

SOUTHWEST -SOUTH EAST

$$\begin{bmatrix} -2,-1,0 \\ -1, 0, 1 \\ 0, 1, 2 \end{bmatrix} \begin{bmatrix} 0, 1, 2 \\ -1, 0, 1 \\ -2,-1,0 \end{bmatrix}$$

VERTICAL-HORIZONTAL

$$\begin{bmatrix} -1, -2,-1 \\ 0, \quad 0, 0 \\ 1, 2, 1 \end{bmatrix} \begin{bmatrix} -1,0,1 \\ -2,0,2 \\ -1,0,1 \end{bmatrix}$$

NORTHEAST -NORTH WEST

$$\begin{bmatrix} 2, 1, 0 \\ 1, 0, -1 \\ 0,-1,-2 \end{bmatrix} \begin{bmatrix} 0,-1,-2 \\ 1, 0,-1 \\ 2, 1, 0 \end{bmatrix}$$

Fig.5. Multi-Sobel kernel of 3×3 dimension

When we deploy the Gaussian filter through convolution in a CNN layer, each output pixel is computed as a weighted sum of its neighboring pixels in the input. Fig . 6 shows the sample features extracted on the corner point using one of the kernels. The convolution operation involves sliding the kernel over the input image, computing the element-wise product, and summing the results to obtain the output. The convolution operation with a Sobel kernel *K* at position (*i*, *j*) in the output feature map can be defined as Equation (1).

$$Output(i,j) = \sum_{m=-M}^{M} \sum_{n=-N}^{N} \; Input(i+m, j+n) \times (m,n) \tag{1}$$

M and *N* are the dimensions of the Sobel kernel, and Input (*i*+*m*, *j*+*n*) is the input value at position (*i*+*m*, *j*+*n*). Output (*i*, *j*) matrix determinant/variance is extracted. Sobel kernels on corner points usually simulate NiN (Network in Network) behavior. NiN uses the same initial convolution sizes as AlexNet. The kernel sizes are 32 × 32 and 3×3 respectively and the numbers of output channels match those of AlexNet. Each NiN block is followed by a max-pooling layer with a stride of 2 and a window shape of 3×3 [13]. The proposed architecture for feature extraction using multi-Soble kernels implemented through CNN can be seen in Fig. 7.

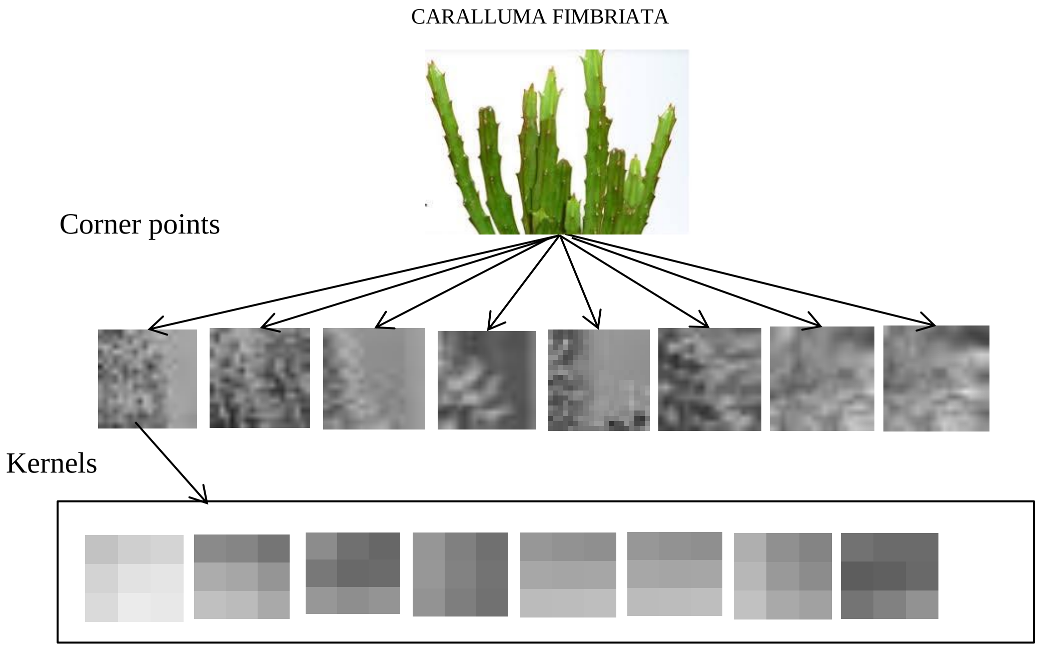

Fig. 6. Corner point and kernel - sample 3×3 features.

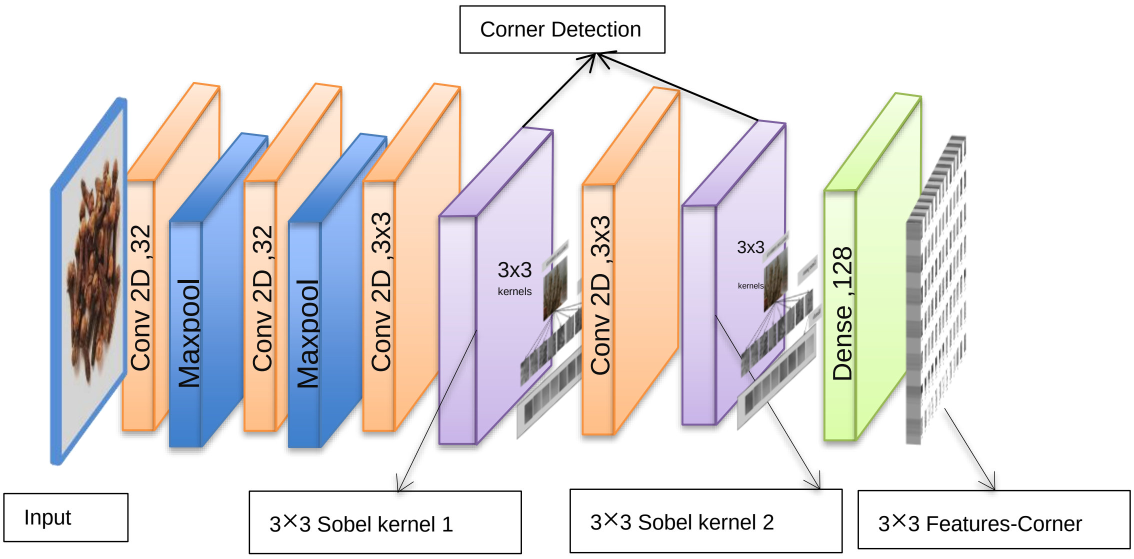

Fig.7. Proposed Architecture custom CNN 3×3-Sobel kernal-layer, Corner detection

3.2. Adaptive Convolutional Neural Network for Corner Detection

In this work, an adaptive CNN is designed with a modified feature set extracted from the corners. The block diagram of adaptive CNN layers shown in Fig. 7 comprises the following key elements.

Each layer functions hierarchically in the direction from left to right. The input image is fed to the first layer. The second layer generates a feature map for the input images supplied by the first layer. With the fundamental building block of CNNs Conv2d and MaxPool2D layers, we introduce *custom kernels*. Custom kernels are the core mutation of the proposed method. The Conv2D layer performs a convolution operation on the input data. Convolution involves sliding a small window (kernel or filter) over the input data and computing the element-wise product between the kernel and the input at each position. As the network learns during training, the filters in the convolutional layer adapt to recognize hierarchical features in the input. The MaxPooling2D layer is used for down sampling or spatial pooling. It reduces the spatial dimensions of the input while retaining the most important information. The pooling involves sliding a window (pooling window) over the input and taking the maximum value within each window. This reduces the size of the feature map while preserving the dominant features.

This proposed CNN model consists of 12 layers, 2 Maxpool, 4 Conv2D, 2 custom Gaussian kernels out of 8 randomly, 1 rescaling, 1 flattened, and 2 dense layers each layers are organized with the best fit in terms of features. We use activation functions including ReLU (Rectified Linear Unit), and Sigmoid. The activation function introduces non-linearity to the model, enabling it to learn more complex relationships in the data. Max pooling strategies are utilized to down-sample the feature maps. Flattening involves reshaping the 3D tensor into a 1D tensor and preparing the data for the fully connected layers that follow. This stage is after 2 custom kernel layers with many tests having 2 kernels improves the efficiency by a very big margin. It surpasses efficiency with more than 2 custom kernel layers. The dense -128 layer matches global patterns and relationships in the data, whereas the Dense 8 layer will reduce the pattern to work with 8 different kernels further.

3.3. Classification of Spices Images

Combining corner detection with convolutional kernels and hidden layers in a Convolutional Neural Network (CNN) involves creating a custom architecture that incorporates corner detection as a part of the feature extraction process. The proposed classification is performed in two stages. The input layer reads the image and forwards it to the next layer. As stated in architecture there are 3 hidden layers used commonly. Cov2D and Maxpool layer use their regular shape and objects to identify feature sets. The corner detection module is integrated with cnn layer at the initial stage. This layer uses specific convolutional filters/kernels in the next layer. These layers are responsible for learning hierarchical features from the corner-enhanced input. The hidden layer manages to transform the input features into processed features and makes it a fully connected neural network. These layers allow the network to learn complex relationships and patterns from the features extracted in earlier layers. The final output layer generates feature sets for the classification of seven spices and the Caralluma fimbriata class.

4. Experimental Results

Since this is a joint work of computer science and food technology, we collected datasets from food technology experts, and the images were labelled by them for authentication and verification. To validate the proposed method, we calculated the classification rate and compared it with the state-of-the-art methods, which are discussed in the subsequent sections.

4.1. Dataset and Evaluation

Our dataset includes seven classes of different spices, namely, clove, cinnamon, kokum, ginger, citrus powder, and jeera, and one more class of Caralluma Fimbriata. The problem is of class classification. Each class consists of 800 images. In total, 6400 sample images were for experimentation. The dataset ensures that the collection of samples represents the possible variations in the images including intra-class and inter-classes. Our dataset includes images captured in different situations, time and locations and hence the dataset is complex for classification. It can be noticed from the samples shown in Fig. 8, where one can see variations within the samples. For evaluating the performance of the proposed method, we use a confusion matrix and classification rate which are standard measures for validating the classification methods. To show the superiority of the proposed method to the existing methods, we implemented two state-of-the-art methods called Gom-Os, (2023) which was developed for fruit image classification using depth information, and Mallikarjun et al. (2022) which was developed for areca nut disease identification using multi-gradient kernels. The reason to choose these two methods for the comparative study is that the objective of the method is the same as the proposed method and the fruit and areca nut images share almost the same properties of texture in different spice images. Further, we implemented one more state-of-the-art method (Singh et al. 2024), which was developed for general image classification for making a comparative study. This method includes ten visual recognition tasks for classification. The motivation to compare the proposed method with this method is to show that the models developed for general image classification may not be effective for the classification of images of different spices.

Fig .8. Sample successfully classified images of each class.

4.2. Ablation Study

In this work, the key steps are corner detection to reduce the complexity of the problem without losing vital information, and multi-Sobel kernels for feature extraction to classify the different spice images. And, there is a need for experiments to show the effectiveness of corner detection, especially processing time. The average classification rate of each class and mean of the average classification rate for all eight classes using the proposed method with our corner detection step and the proposed method with Harris corner detection step are reported in Table 1. It is observed from Table 1 that the results of the proposed method with our corner detection are better for all the classes compared to the result of the proposed method with Harris corner detection. This shows that our corner detection is robust to spice images while the existing Harris corner detection does not. This makes sense because the Harris corner detection was designed for high-quality images but not low-quality spice images.

In the same way, the results of different Sobel kernels reported in Table 2 show that the average classification rate is almost similar for both types of kernels for all the classes. Therefore, one can infer that both types of kernels contribute equally to the classification of spice images and both kernels are important to achieve the best classification results. The response time per image and for the whole dataset reported in Table 3 for the proposed method with our corner detection and the proposed method with Harris corner detection show that our method with corner detection consumes less time compared to Harris corner detection. Since the existing Harris corner detection is not robust, it requires more time to process images compared to our corner detection. Therefore, we can argue that the proposed method is effective and efficient for the classification of different spice images. The following system configuration is used for all the experiments in this work.

System Specification, Software: OS: Linux Mint 21.0 Mate, Editor: VSCODE 1.85, Python: 3.10.12. **Hardware:** Processor: AMD Ryzen 3200G @3.6GHz, Ram: 8GB, HDD: 1TB.

Table 1. Average Classification Rate of the Proposed Method with our Corner Detection and the Proposed Method with Harris Corner Detection on our Dataset in (%).

Class	Steps	
	The proposed method with our corner detection	The proposed method with Harris corner detection
CARALLUMA FIMBRIATA	99.99	92.5
CINNAMON	99.74	93.23
CITRUS PEEL	99.94	98.12
CLOVE	99.89	89.54
GINGER	97.8	90.04
JEERA	98.12	78.1
KOKUM	100	82.52
MINT	99.99	98.65
Mean of Average classification rate	99.43	90.33

Table 2. Average Classification Rate of Individual Sobel kernels in (%)

Classes	Multi-Sobel Kernels	
	With Kernel 1 and 2	With Kernel 3 and 4
CARALLUMA FIMBRIATA	99.99	98.99
CINNAMON	99.74	99.74
CITRUS PEEL	99.94	99.94
CLOVE	99.89	99.89
GINGER	97.8	97.8
JEERA	98.12	98.12
KOKUM	100.00	92.23
MINT	99.99	97.83
Mean of Average Classification Rate	99.43	98.06

Table 3. The Response Time of the Proposed Method with our Corner Detection and the Proposed Method with Harris Corner Detection

Experiments	The proposed method with our corner detection	The existing method with Harris corner detection
Average time for corner detection in a single image	2 sec	9 sec

The average time taken in work with 8 class Dataset	17 sec	79 sec

4.3. Experiments on Classification

Confusion matrix and average classification rate are computed for the proposed and existing methods (Mallikarjuna et al. 2022, Gom-Os, 2023 and Singh et al. 2024) for all the classes are reported in Table 4-Table 7, respectively, where it is noted that the proposed method is the best compared to the existing methods. This makes sense because the features extracted in the existing methods are not robust and may not be effective for the classification of spice images. The main challenge of spice images is that the pattern within the image varies, and it is not predictable. Therefore, the features extracted by the existing methods do not work well for the classification. Since the primary objective of the existing methods is different from the proposed method, the existing models are not effective for the classification of spice images. On the other hand, the use of new ideas of corner detection to reduce the complexity of the problem and the feature extraction using multi-Sobel kernels is key for the successful classification of different spice images. The same inferences can be drawn from the results. average classification rate of each class and the mean of the average classification rate of all the classes reported in Table 8. In Table 8, it is noted that the method (Singh et al. 2024) is the best among all other existing methods in terms of the mean of average classification rate. This is valid because the method (Singh et al. 2024) explores a powerful deep-learning model and trains with billions of samples to make it more generic compared to other existing methods. However, its performance is worse than the proposed method. The key reason is that the classification of images of different spices is on general images while the proposed method requires specific features for successful classification.

Table 4. Confusion Matrix and ACR (in %) of the Proposed Method for Classification of Spices and Caralluma Fimbriata

Class	CARALLUMA FIMBRIATA	CINNAMON	CITRUS PEEL	CLOVE	GINGER	JEERA	KOKUM	MINT
CARALLUMA FIMBRIATA	99.75	0.00	0.00	0.00	0.00	0.00	0.00	0.25
CINNAMON	0.00	99.63	0.00	1.75	0.62	0.00	0.00	0.37
CITRUS PEEL	0.00	1.12	100.00	4.24	0.25	0.00	0.00	0.00
CLOVE	0.00	1.50	3.25	100.12	0.12	1.50	0.62	0.00
GINGER	0.00	0.00	0.00	1.00	99.25	0.50	1.25	0.00
JEERA	0.62	1.00	1.00	0.00	1.12	94.13	0.00	0.00

KOKUM	0.00	0.00	0.25	0.00	0.25	0.00	98.50	0.25
MINT	0.00	0.62	0.00	0.00	0.00	2.75	1.37	100
ACR	99.43%							

Table 5. Confusion Matrix and ACR (in %) of the Existing Method Mallikarjuna et al. (2022) for Classification of Spices and Caralluma Fimbriata

Class	CARALLUMA FIMBRIATA	CINNAMON	CITRUS PEEL	CLOVE	GINGER	JEERA	KOKUM	MINT
CARALLUMA FIMBRIATA	81.27	3.37	4.00	1.50	1.87	5.74	1.62	0.62
CINNAMON	3.25	82.90	2.50	4.74	1.25	4.49	3.75	1.00
CITRUS PEEL	4.99	1.75	85.39	4.24	2.87	6.99	2.87	1.37
CLOVE	2.87	1.50	3.25	88.89	1.00	2.50	5.62	1.87
GINGER	5.62	3.12	1.50	1.00	91.01	6.99	2.87	1.00
JEERA	1.62	2.25	2.25	0.00	1.12	61.67	0.00	1.25
KOKUM	1.37	0.00	1.62	2.12	1.50	13.73	82.90	0.87
MINT	0.00	2.00	1.87	1.50	2.00	2.75	1.37	93.01
ACR	83.38%							

Table 6. Confusion Matrix and ACR (in %) of the Existing Gom-Os, (2023) for Classification of Spices and Caralluma Fimbriata

Class	CARALLUMA FIMBRIATA	CINNAMON	CITRUS PEEL	CLOVE	GINGER	JEERA	KOKUM	MINT
CARALLUMA FIMBRIATA	77.78	4.37	5.24	4.00	2.00	5.74	1.87	1.75
CINNAMON	3.00	84.14	3.12	2.25	1.87	4.49	3.75	1.00
CITRUS PEEL	4.99	1.75	76.15	4.24	1.37	6.99	2.87	1.37
CLOVE	2.87	5.37	4.24	80.52	6.12	6.24	8.11	1.87
GINGER	5.62	3.12	4.24	3.50	86.02	6.99	2.87	5.99
JEERA	4.87	3.50	4.24	4.99	1.12	44.19	29.96	2.50
KOKUM	1.37	5.62	1.62	2.12	1.50	11.24	77.28	2.12
MINT	1.50	5.62	4.24	2.75	5.37	2.75	1.37	89.26
ACR	**76.12%**							

Table 7. Confusion Matrix and ACR (in %) of the Existing Singh, et al. (2024) for Classification of Spices and Caralluma Fimbriata

Class	CARALLUMA FIMBRIATA	CINNAMON	CITRUS PEEL	CLOVE	GINGER	JEERA	KOKUM	MINT

CARALLUMA FIMBRIATA	92.13	1.87	1.25	0.62	1.37	0.62	1.87	0.25
CINNAMON	1.25	87.27	1.87	1.00	1.12	2.25	3.75	1.50
CITRUS PEEL	1.50	0.62	90.26	0.50	1.37	2.87	1.87	1.00
CLOVE	0.37	1.37	1.75	91.01	0.50	1.87	2.12	1.00
GINGER	0.37	0.62	0.00	1.00	97.13	0.00	0.75	0.12
JEERA	1.00	2.12	1.75	3.00	1.75	77.90	12.23	0.25
KOKUM	1.00	0.37	0.50	0.87	1.50	4.37	89.26	2.12
MINT	0.00	0.00	0.50	0.25	0.00	0.62	0.25	98.38
ACR	**90.5%**							

Table 8. Average Classification Rate for Comparative Study of the Proposed Method with the State-of-the-art methods in (%)

Class	Methods			
	Proposed method	Mallikarjuna et al. (2022)	Gom-Os, (2023)	Singh et al. (2024)
CARALLUMA FIMBRIATA	99.99	82.00	78.00	92.3
CINNAMON	99.74	86.00	82.00	87.5
CITRUS PEEL	99.94	84.00	76.00	90.23
CLOVE	99.89	88.00	79.00	91.3
GINGER	97.8	90.00	81.00	97.4
JEERA	98.12	61.00	58.00	77.95
KOKUM	100.00	84.00	71.00	89.44
MINT	99.99	92.00	84.00	98.32
Mean of Average Classification Rate	99.43	83.38	76.12	90.5

To test the robustness of the proposed method, we rotated images randomly and added random Gaussian noise to show the proposed method is invariant to rotation and noise to some extent. The proposed and existing methods are tested on rotated and noisy images and the results are reported in Table 9. Here it is noted that the results of the proposed method on different rotation and noisy images are almost the same as the normal images, while the result of existing methods drops significantly for rotated and noisy images. This indicates that the proposed method is robust when compared to the existing methods. On the other hand, the existing methods are not robust to different rotations and noisy images for classification of images of different spices.

Table 9. Performance of the Proposed and Existing Methods on Different Rotations and Noisy Images in (%).

Dataset	Methods			
	Proposed method	Mallikarjuna ,et al. (2022)	Gom-Os, (2023)	Singh, et al. (2024)
Dataset-1: Original	99.43	83.38	76.12	90.5
Dataset-2: Rotated	98.14	82.00	76.43	89.42
Dataset-3: Gaussian Noise	94.15	79.56	75.56	77.95

Limitation: Sometimes the images lose texture pattern as shown in Fig. 9, where we can see the texture pattern is lost due to sparse and the wide gap between the elements in the images. Although the corner detection step works well, the feature extraction step loses vital information that is required for discrimination. This is beyond the scope of the present work and hence there is scope for improvement. In this situation, one should think of a method that can work even if a small amount of information is present in the images. One of the ways is to segment the elements in the image first and then use the segmented region as input for feature extraction followed by classification. Our future work will focus on this aspect.

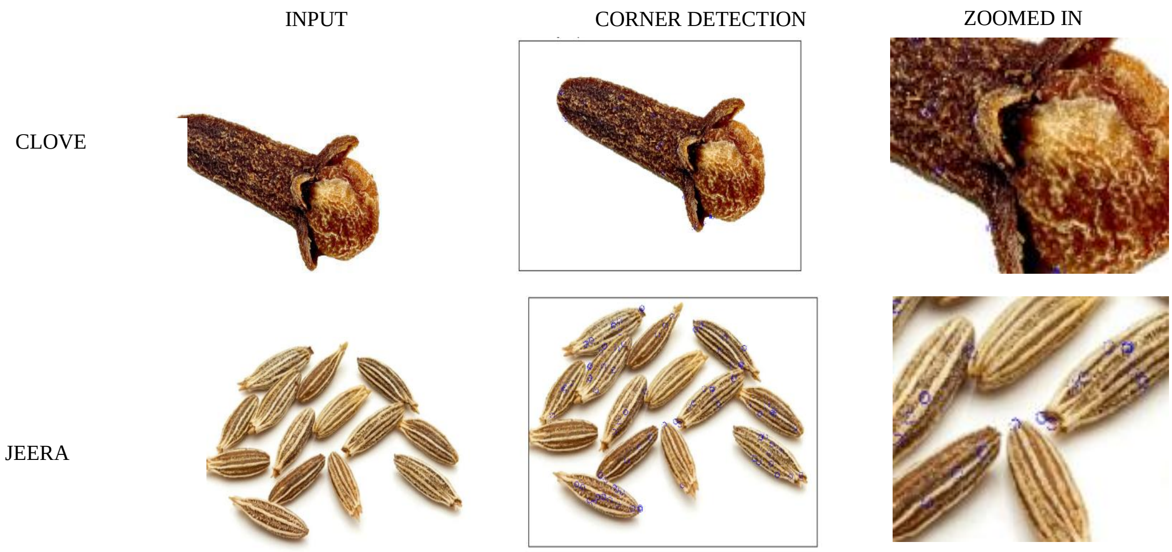

Fig.9. Failure Case of Classification

5. Conclusion and Future Work

We have proposed a combination of corner detection, feature extraction using multi-Soble kernels, and adaptive convolutional neural networks for the classification of seven species and one more class Caralluma Fimbriata. It is a class classification problem. We explored distance measure and

Gaussian distribution for detecting corners in the images with the help of the Canny edge image. Multi-Sobel kernels were used for feature extraction by considering corners as input. The features are fed to the convolutional neural network for classification. The advantage of the present work is that to implement the above steps, we adapted CNN. This is new compared to the existing works. The proposed method is tested on our dataset for classification and compared with the state-of-the-art methods. The results show that the proposed method is outstanding compared to the existing methods. However, when the image loses its texture pattern due to sparse and loss of elements in the images, the proposed method fails to perform. This can be solved by introducing a segmentation step to locate the vital region in the images that feature extraction followed by classification. Another way is to explore deep -learning which works well for sparse information. Our future work could be in this direction.

Acknowledgements

The authors express their sincere gratitude to Prof. Dr. B. D. Kumbar, Hon'ble Vice Chancellor, Davangere University, Davangere, for motivating us to take up inter-disciplinary research work and thus the present work is the collaborative effort of the Department of Studies in Computer Science and the Department of Studies in Food Technology Davangere University, Davangere.

References

Anitha E, Nandhini S, sHari Kumar Palani and Marshal Mano C, ”Recipe Recommendation using Image Classification”, In Proc. ICIRCA ,pp 292-296,2023.

Anwar. R, Rabail. R, Rakha. A, Bryla.M, Roszko M, Aadil.R. M & Kieliszek. M,” Delving the role of Caralluma Fimbriata: An edible wild plant to mitigate the biomarkers of metabolic syndrome”. Hindawi, Oxidative Medicine and Cellular Longevity, pp 17,2022.

Ashwath, V. A., Sikha, O. K and Raul Benitez, ”TS-CNN: A Three-Tier Self-Interpretable CNN for Multi-Region Medical Image Classification”, IEEE in Medicine and Biology Society section, pp 78402-78418, 2023.

Ayan Mukherji, Arindam Mondal, Rajib Banerjee and Saurav Mallik, “Recent Landscape of Deep Learning Intervention and Consecutive Clustering on Biomedical Diagnosis”, Artificial Intelligence and Applications, pp 1-17 ,2023.

Chuang Niu, Hongming Shan and Ge Wang “SPICE: Semantic Pseudo-Labeling for Image Clustering”, IEEE Transactions on Image Processing, pp 7264-7279,2022.

Elena Denny Cherpanath, Fathima Nasreen P R, Karthika Pradeep, Malavika Menon,Dr. Jayanthi V S,”Food Image Recognition and Calorie Prediction using Faster R-CNN and Mask R-CNN”, In Proc. ICSCC, pp 83-90, 2024.

Fotios S. Konstantakopoulos, EleniI George, Dimitrios I. Fotiadis,” An Automated image -Based Dietary Assessment System for Mediterranean Foods”. In Proc. EMB, pp 45-55, 2023.

Gom-Os, D. F. K. “Fruit Classification using Colorized Depth Images”, International Journal of Advanced Computer Science and Applications, pp 1023-1032, 2023.

Ira Safira, Muhathir,“Analysis of Different Naïve Bayes Methods for Categorizing Spices Through Photo using the Speeded-up Robust Feature”, In Proc. ICCoSITE, pp 29-35, 2023.

Jana S, Shanmukha Nagasai P, Saravan Kumar K and Mani Nageshwar V, “Categorization and Grading of Spices using Deep Learning”, In Proc. ICDSIS, pp 133-138 .,2022.

Jie Du, Kai Guan, Yanhong Zhou, Yuanman Li, and Tianfu Wang, “Parameter-Free Similarity-Aware Attention Module for Medical Image Classification and Segmentation”, In Proc. TECI, pp 845-857, 2023.

Kaharuddin, Kusrini,Vera Wati,Elvis Pawan and Patmawati Hasan”Classification of Spice Types Using K-Nearest Neighbor Algorithm”, In Proc. ICOIACT ,pp 285-291, 2019.

Lim S.H, Lee H.S, Lee C.H & Choi C.I “Pharmacological activity of Garcinia indica (Kokum): An updated review”, Pharmaceuticals, pp 1338, 2021.

Mallikarjuna, S. B., Shivakumara, P., Khare, V., Basavanna, B., Pal, U and Poornima, B. “Multi-gradient-direction based deep learning model for Areca nut disease identification”, CAAI Transactions on Intelligence Technology, pp 156-166, 2022.

Mao Q. Q., Xiao X.Y, Cao S.Y, Gan R. Y, Corke H, Beta T, & Li H. B. “Bioactive compounds and Bioactivities of Ginger (Zingiber officinale Roscoe). Foods”, 2019.

Maryam Asadzadeh Kaljachi, Arnab Halder, Umapada Pal and Palaiahnakote Shivakumara,” Spatiotemporal Edges for Arbitrarily Moving Video Classification in Protected and Sensitive Scenes”, Artificial Intelligence and Applications, pp 1-8, 2023.

McKay D.L & Blumberg J.B “A review of the bioactivity and potential health benefits of peppermint tea (Mentha piperita L)”. Phytotherapy Research, pp 619-633, 2006.

Md. Maruf Hasan Talukder, Tania Aktar Ria, Md. Mehedi Hasan, Md. Hamidur Rahman, Abdus Sattar.” A Computer Vision and Deep CNN Modeling for Spices Recognition”, In Proc. ICCCNT, pp 54827-54832,2022.

Muhammad Insan Al-Amin, Fahmi Nur Sidiq, Diena Rauda Ramdania, Nurmalik Fajar, Yana Aditia Gerhana and Maisevli Harika,” Spices Image Classification Using Support Vector Machine”, In Proc. ICITSM, pp 1-4 ,2022.

Muhlis Tahir, Abdul Azis Jakfar, Dian Budi Elnursa and Rio Meisya Resnanda. ”Performance Evaluation of Pre-trained Convolutional Neural Network and Transfer Learning for Classification of Spices and Herbal Medicines in Madura”, In Proc. ICOSNIKOM, pp 60230-60235, 2023.

Natesan P, Thamil Selvan Lihua Luo,” Research on Food Image Recognition of Deep Learning Algorithms”, In Proc. CIPAE, pp 733-737, 2023.

Panda, B., Mishra, M. N., Mishra, B. S. P and Tiwari, A. K (2023). “Optimized Convolutional Neural Network for Robust Crop/Weed Classification”. International Journal on Pattern Recognition and Artificial Intelligence.

Park G.H, Lee S.H, Kim H.Y, Jeong H.S, Kim E.Y, Yun Y.W & Lee B. J “Comparison in antioxidant effects of four citrus fruits”. Journal of Food Hygiene and Safety, pp 355-360, 2011.

Potadar, M. P and Holambe, R. S (2023). ”Automatic Multi-Class Brain Tumor Classification Using Residual Network-152 Based Deep Convolutional Neural Network”, International Journal on Pattern Recognition and Artificial Intelligence.

Pranav Kathar, Rajshree Khandare, Manisha Das and Deep Gupta,” Vision Outlooker-based Hierarchical Food Classification”, In Proc. TENCON, pp 317-323, 2023.

Rahaman Soroush and Yasser Baleghi, “Ensemble learning for multispectral scene classification”, International Journal of Pattern Recognition and Artificial Intelligence, 2022.

Ramkumar, G., Manonmani, V., Sakthisaravanan. N, Venkatramanan C B, S. Palanivel and ATA Kishore Kumar,” A Real-time Food Image Recognition System to Predict Calories by Using Intelligent Deep Learning Strategy “, In Proc. ICRMKM, pp 1-7, 2023.

Romario Sameh Samir Anwar," EfficientNet Algorithm for Classification of Different Types of Cancer", Artificial Intelligence and Applications, pp 1-10, 2023.

Sasikumar, S., Pugalenthi, R., Sasikala, G. M and Rajakumar, M. P (2023). "Medical Image Segmentation and Classification Using Modified DoubleU-Net and PolyNet Deep Neural Networks", International Journal on Pattern Recognition and Artificial Intelligence.

Shinwari Z. K, Sultan. S & Mehmood. T "Molecular and morphological characterization of selected Mentha species". Pak. J. Bot, pp 1433-1436, 2011.

Shrivarshini, R., Dhanya B. and Kalaiselvi S." Prediction of Healthy and Unhealthy Food Items using Deep Learning", In Proc. ICCMC, pp 233-239, 2023

Singh, M., Duval, Q., Alwala, K. V., Fan, H., Aggarwal, V., Adcock, A., Joulin, A., Dollár, P., Feichtenhofer, C., Girshick, R., Girdhar, R and Misra, I (2024). "The effectiveness of MAE pre-pretraining for billion-scale pretraining", In Proc. ICCV, pp 5484-5494.

Socher R, Perelygin A, Wu J, Chuang J, Manning CD, Ng AY, Potts C. "Recursive deep models for semantic compositionality over a sentiment treebank". In Proc. EMNP, pp 1631–42, 2013.

Soumi Das, Palaiahnakote Shivakumara, Umapada Pal, Raghavendra Ramachandra," Gaussian Kernels based Network for Multiple License plate number detection in day-Night images", In Proc. ICDAR, pp 70-87, 2023.

Srinitya, G., Sharmila, D., Logeswari, S and Daniel Madan Raj, S. "Automated SAR image segmentation and classification and using modified deep learning", International Journal of Pattern Recognition and Artificial Intelligence, 2023.

Srinivasan, K. "Cumin (Cuminum cyminum) and black cumin (Nigella sativa) seeds: traditional uses, chemical constituents, and nutraceutical effects", Food quality and safety, pp 1-16, 2018.

Weijie Yang and Yueting Hui, "Image scene analysis based on improved FCN model", International Journal of Pattern Recognition and Artificial Intelligence, 2021.

Xun Sun, Baojiang Zhong," A Rotation-Invariant Corner Detector Based on the Median of Sub Pixelated Triangle", Journal of King Saud University, 2023.

Yan-e Hou, Kang Yang, Lan Xue Dang and Yang Liu," Contextual Spatial-Channel Attention Network for Remote Sensing Scene Classification", pp 6608805, 2023.

Yi-Cheng Huang,Yi-Cheng Huang,Kuo-Chun Hung Chun-Chang Liu ,Ting-Hsueh Chuang, Shean-Juinn Chiou , "Customized Convolutional Neural Networks Technology for Machined Product Inspection", MDPI , pp 6-12, 2022.

Yuqun Yang, Xu Tang, Yiu-Ming Cheung, Xiangrong Zhang and Licheng Jiao,"SAGN: Semantic-Aware Graph Network for Remote Sensing Scene Classification", IEEE Transactions on Image Processing, pp 1011-1026, 2023.

Zeiler MD, Fergus R. "Visualizing and understanding convolutional networks", In Proc. ECCV, pp 818–33, 2014.

Zhu, J., Liu, Q and Xu, C (2023). "Graph Convolutional Neural Network with Multi-Scale Attention Mechanism for EEG-Based Motion Imagery Classification", International Journal on Pattern Recognition and Artificial Intelligence.