IJIRIS: International Journal of Innovative Research in Information Security
Volume 10, Issue 04, May 2024
E-ISSN: 2349-7017
P-ISSN: 2349-7009
https://www.ijiris.com/archives

Detection of Rice Varieties using Deep Neural Network

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Publication History
Manuscript Reference No: IJIRIS/RS/Vol.10/Issue04/MYIS10120
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRIS/RS/Vol.10/Issue04/MYIS10120
Received: 17, April 2024 | Revised:30, April 2024 | Accepted: 07, May 2024 Published Online: 30, May 2024 Volume2024
Article ID MYIS10120 http://www.ijiris.com/volumes/Vol10/iss-04/41.MYIS10120.pdf
Article Citation: Deepak,Dr.Shivani,Kumar,Mayur(2024). Detection of Rice Varieties using Deep Neural Network. International Journal of Innovative Research in Information Security, Volume 10, Issue 04, Pages 635-640
doi:> https://doi.org/10.26562/ijiris.2024.v1004.41
BibTex key: Dr.Shivani@2024Detection

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Abstract: Rice is a staple food in southern India, and there are many types of rice grown in the region to meet the needsof the developing population. Despite significant investments in land, labor, equipment and materials, farmersoften face huge losses due to factors such as climate change, drought, and poor seed quality. Traditionally,seed quality is assessed by Seed Testing Laboratories (STL), where purity analysis is performed without automation and manually byexperts. However, this manual process can be inconsistent between laboratories depending on the expert'sfatigue,visual perception, and personal circumstances. To solve these problems, electronic systems areneeded to identify types of seeds and products to control the quality of planting [1]. This study presents a methodto classify rice varieties in the southern Indian state of Tamil Nadu using a deep neural network and aubiquitous photo processing technique called RiceSeedNet. A custom corpus, called the RiceSeed Photo corpus, was created containing 75,000 photos representing 5 local crops,15,000 photos per species. Using a photo converter-based architecture, RiceSeed Net achieved accuracy in identifying these 5 species. Additionally, RiceSeed Net demonstrated its effectiveness on different datasets by achieving accuracy in identifying 8 varieties when testing population data on different rice varieties [2].

Keywords: Deep neural network, vision transformation, grain classification, precision agriculture, photo processing, machine vision, CNN.

INTRODUCTION

Rice holds a crucial role in global food security due to its widespread consumption. Its quality and traits vary significantly based on environmental factors like temperature, humidity, and soil quality across regions. Accurate classification of rice types is essential for optimal results [3]. Various methods are employed, including visual assessment, morphological analysis, and evaluation of attributes such as color, shape, taste, aroma, and nutritional content. Despite the expertise of farmers and specialists in discerning rice types, reliance solely on manual methods can be inefficient and error prone. Therefore, automated systems leveraging advancements in machine learning have emerged as a promising solution [4]. These systems utilize deep learning and image analysis techniques to categorize rice varieties accurately and efficiently based on visual characteristics like texture, shape, and color. Classification traditionally involves sorting rice based on size (long, medium, or short grain) and stickiness. Genetic variations also play a significant role, with indica rice having long, non-sticky grains, and japonica rice featuring short, sticky grains. Multigrain analysis enhances classification accuracy by considering multiple characteristics simultaneously [5]. Machine learning algorithms, particularly convolutional neural networks (CNNs), have revolutionized rice classification by learning hierarchical representations from images. These networks excel at identifying distinguishing features like texture, shape, and color, leading to more precise classification outcomes [6].

A notable advancement is the integration of spatial spectral deep CNNs, which combine spatial and spectral information to further refine classification accuracy. Despite their efficacy, machine learning algorithms face challenges such as processing large datasets, handling nonlinear data, and discerning relevant information from irrelevant data. However, ongoing developments in deep learning continue to enhance the accuracy and efficiency of rice classification systems, offering promising prospects for improving food security globally. Using spatial and spectral features, these networks can improve accuracy by detecting different visual patterns for different types of rice. In fact, the automation, scalability, and generalization capabilities of deep learning are highly valued by the scientific community, and with the continuous development of deep learning, these methods are crucial for the advancement of deployment. Distribution: however, identification of rice seeds remains to be investigated [7]. This difference is caused by many challenges such as lack of open-source data, class inconsistencies, limited data volume, and classification errors. Additionally, local crops in a region need to be differentiated quickly. To address these issues, we developed RiceSeedNet, a visual transformation (ViT) model using the bit-patch 32 method, specifically designed to classify 13 rice varieties from Tamil Nadu, India. RiceSeedNet achieves 97% accuracy on test data. The model uses the Transformer architecture to extract features from photo blocks, while a custom-designed neural network controls classification via backpropagation. We collected photos of 13 native species using smartphone cameras to create a database of rice seeds, resulting in more than 15,000 photos. Photos were processed to separate individual genes as well as entire clusters containing more than 60 genes. Additionally, the model performs very well from cross-validation data, achieving 99% accuracy on open data for eight Asian rice species [8]. Extensive and diverse data, combined with robust testing, ensures the reliability and accuracy of models in real-world environments. The architecture of ordinary neural networks is powerful enough to use a non-linear "activation function" with weight and bias for the output of each layer. The number of weights in a normal neural network is calculated at each level depending on the number of layers in the network and the type of function used, such as the ReLu function, logistic function, or hyperbolic tangent function (tanh) [10]. This model was developed using artificial neural networks (ANN) and deep neural networks (DNN) for specific photos, and convolutional neural networks (CNN) for dataset photos. Machine photos combined with neural networks, where the training is done by a neural network instead of humans.

RELATED WORKS:

In recent years, the automated sorting of rice has gained significant traction, driven by the rising demand for rice and the imperative for improved agricultural practices. These sorting machines are designed to meticulously and efficiently identify grains based on specific attributes such as texture, shape, color, and other visual characteristics. They leverage advanced technology and methodologies, playing a pivotal role in advancing the broader objectives of precision agriculture [12]. Machine vision, which empowers computers to interpret visual data and make informed decisions, lies at the core of this technological advancement. Numerous applications of vision technology in agriculture, particularly in crop management, have been extensively documented in the literature [12]. One notable application involves the classification of 14 different products utilizing machine vision, machine learning, and deep learning algorithms. This process encompasses both pre-screening and quality screening stages, aiming to eliminate substandard samples. Among the various models assessed, the deep learning model InceptionResNetV2 demonstrated the highest accuracy, achieving an impressive 95%. Another study conducted by Gilanie et al. featured RiceNet, an enhanced 18-layer convolutional network that attained 100% accuracy in classifying seven rice species in Pakistan.

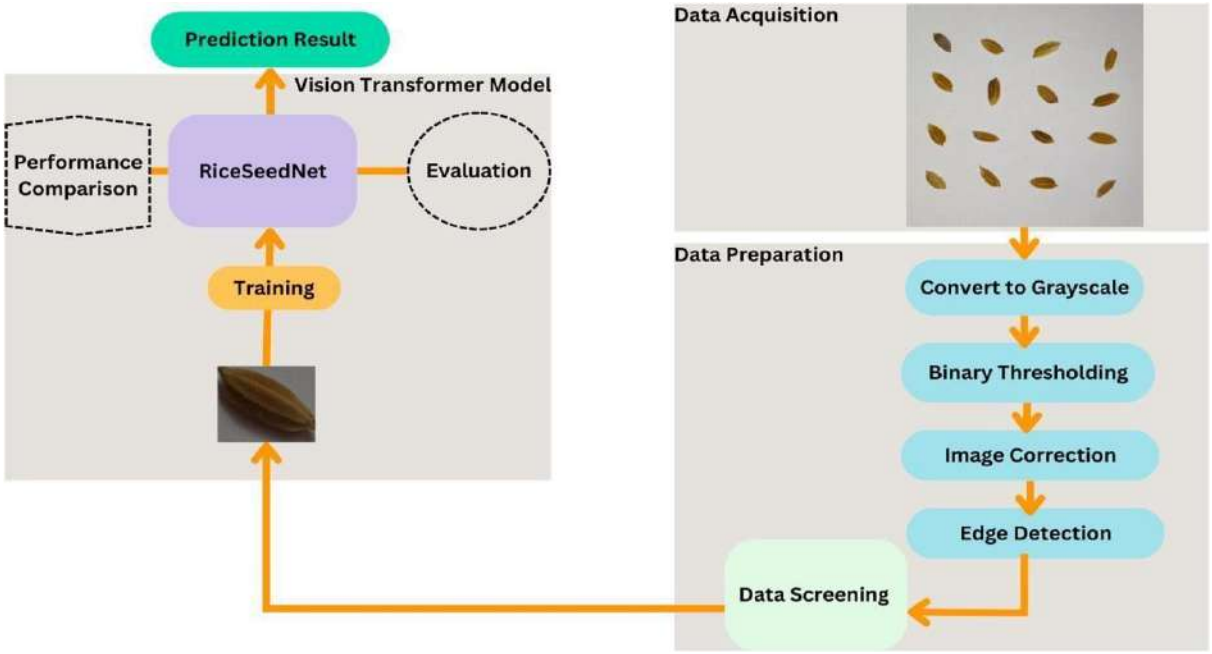

Fig1- System overview

This system utilizes an electronic image generator to capture photographs of sets containing 1, 5, 10, 15, and 20 seeds. Furthermore, another research endeavor focused on three Taiwanese rice varieties (Taikong-9, Tanan-11, and Taikong-14). This study involved gene extraction and employed a backpropagation neural network (BPNN) for classification, achieving accuracies of 92.68%, 97.35%, and 96.57%, respectively. Murat Köklü and colleagues achieved a remarkable 100% accuracy in identifying five types of Turkish rice (Arborio, Basmati, Çeşitli, Jasmine, and Karacada) using neural networks, specifically CNNs [13]. Additionally, they tested the performance of artificial neural networks (ANN) and deep neural networks (DNN), achieving accuracy rates of 99.87% and 99.95%, respectively [18]. Their study utilized two distinct datasets: one comprised 75,000 object images, while the other encompassed 106 features, including morphology, shape, and color characteristics. In a separate study, researchers in Vietnam employed deep learning techniques alongside manual feature analysis to comparatively assess the distribution of six rice species. The DenseNet121 model emerged as the top performer with an accuracy of 99.04%. Furthermore, additional research delved into the utilization of backpropagation neural networks (BPNN) for rice grain classification, leveraging features such as color, texture, and wavelets, achieving accuracy exceeding 96% [15].

This study compares the results with other learning models such as K-Nearest Neighbor, Naive Bayes, and Support Vector Machine. take a test A study using deep convolutional neural networks (D-CNN) and EfficientNet B0 to classify damaged counters into seven categories: healthy, damaged, normally damaged, fully chalky, discolored, half chalky, and discolored: 98.37% The best model with total accuracy. Another study used photo processing to classify four rice varieties: Baldo, Osmancäk, Jasmine and Käräk, and extracted six photos with 90% classification accuracy. Additionally, Shamim et al. Here eight types of rice are classified in different ways; The combined model of different features and the ANN classifier showed 77% accuracy in identifying these species. As you can see from the review, convolutional neural networks are the most popular tools used by scientists to classify grains and seeds into different types. These studies often focus on specific types of rice using small sample sizes.

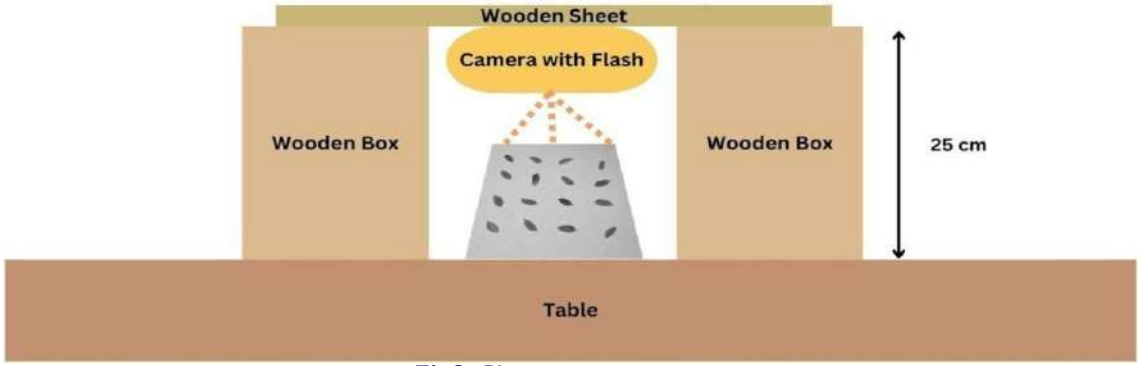

Fig2- Photo acquisition setup

Fig 3- Photo from Camera

In practical applications, the limited size of datasets, typically comprising only a few hundred samples, can introduce biases and errors. Recent research indicates that Vision Transformers have the potential to match or even surpass the performance of CNN-based methods in photo classification tasks [16]. Vision Transformers have shown notable advancements in integration processes, delivering promising results across various metrics for photo retrieval and category-level retrieval. Moreover, investigations into the robustness of Vision Transformers compared to CNNs have yielded positive findings. In our ongoing research, we aim to leverage Vision Transformers in conjunction with image processing techniques to classify different rice seed varieties. We have gathered samples from 13 distinct rice varieties originating from the Indian state of Tamil Nadu. The forthcoming sections will detail the proposed methodology and present our experimental findings.

PROPOSED METHODOLOGY

The RiceSeed Net concept provides a final-to-final system that combines deep neural networks with photo processing techniques, defining each stage of data collection until the final estimation of rice seeds.

DATA COLLECTION:

Images of rice seeds were captured using a 64-megapixel smartphone camera equipped with a Sony IMX682 sensor. This study investigated 13 rice varieties from the southern region of India, including Kothamalli Samba (Kos), Kullagar (Kr), Karunkuruvi (Krn), Kuliadichan (Kun), Open Samba (Ks), Chitrakar (Ch), Chinnal (Central), Milagu Samba (Mas), Mapillai Samba (MP), Norungan (North), SivapuKowuni (Sku), SwarnaMasoori (South), and Yanaikomban (Y). Seeds were carefully arranged on white paper, approximately 100 seeds per photo, to avoid overlapping, as shown inFigure 3. 75% of this data is allocated to education and 25% to exams. Steps: - Processing, geneidentification, and evaluationof gene quality. Photo segmentation is done by inverse binary thresholding by selectingthe threshold value between 110 and 125. Use the Connect tool in OpenCVto create gaps in the photo; This helps define a clear area around the foreground pixels. Precise contours. This process is very important in determining the boundaries of each gene. From this model, measurements such as height, width, and alignment of the bounding box around the seed were obtained. Seedlength is determined bymeasuring from the center to the end of the mass, as shown in Figure. This bounding box fits the values of the points on the edge far thest from the center of the cluster. Using length by length, the height or length of the grain is determined, usually longer than it is wide. Additionally,ellipse fitting is used on the joint model of the object to estimate the size of the genes based on the maj and min axis lengths. These precise measurements help in cultivating the seeds and placing them in a special catalog for furtheranalysis.

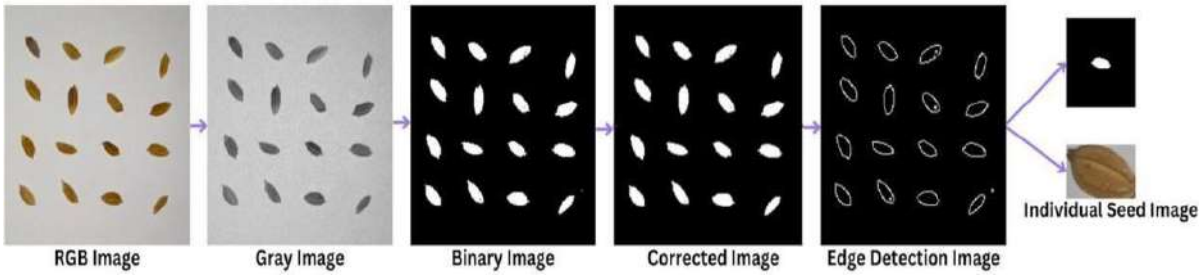

Fig 4- Pre-processing Steps

The Vision Transformer (ViT) model is specifically crafted for computer vision applications, including tasks like image classification, object detection, and image segmentation. Originally designed for natural language processing (NLP), Transformer has made significant advances in computer programming. Historically, neural network networks (CNNs) [17], including architectures such as ResNet, DenseNet, and Inception, were frequently used for tasks such as photo classification. But Transformers introduced a new method that focuses on the relationship between two pairs of input tokens through a machine called maintenance. This feature allows the converter to capture global dependencies in the photo. For the RiceSeedNet, the Vision Transformer operates as outlined and involves the following keysteps:

Patch Extraction: The core photo is divided into large, no-overlapping pieces. Each patch represents aspecificareaofthephoto.

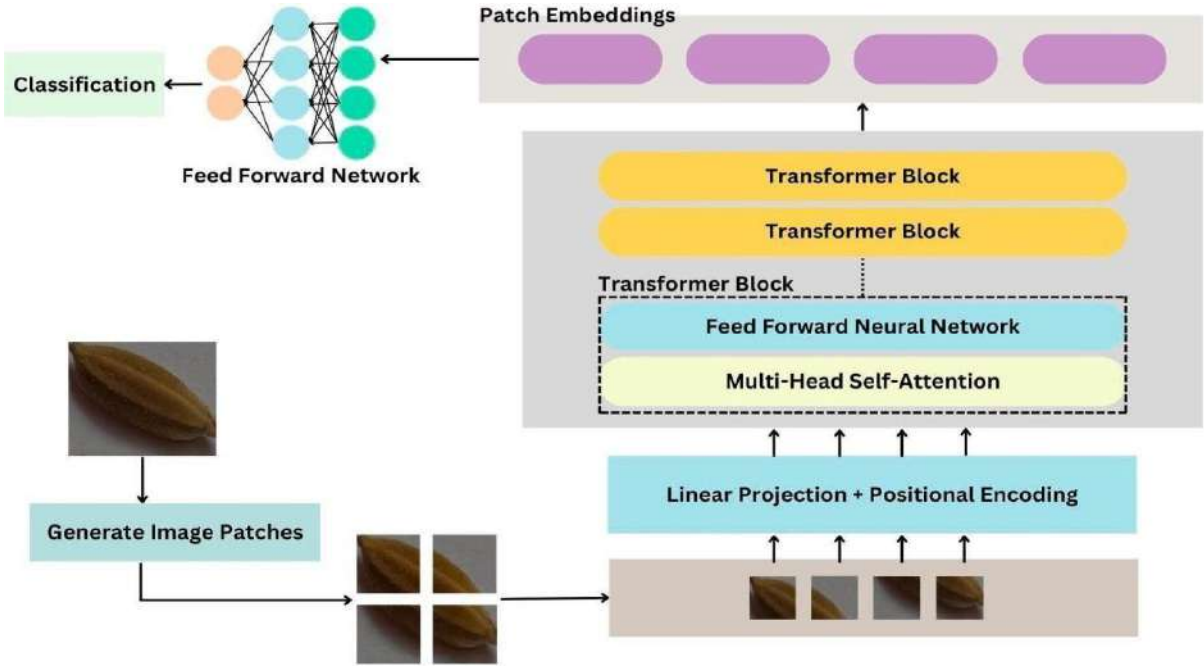

Fig 5- Insight model architecture.

Patch Embedding: Each grain of rice has undergone a transformation, turning it into a low-dimensional representation called photo embedding. This system stores important information about each patch.

Position Embedding: To provide spatial details, location information is added to field embeddings for all rice seeds, encoding the location of each patch.

Sequence Preparation: Embedded patches are combined with their source data to form the input token array. Then the process becomes ready to be completed by the transformer encoder.

Transformer Encoder: This model includes multiple self-monitoring and support neural networks. Self-monitoring allows the model to measure and understand the relationship between different areas of the grain, providing a better view of the context of the world in the photo.

Classification Token: "Tags" are added next to the labels within the scope of photo classification. This labelis learned and represents the entire photo; It plays an important role in classifying rice seeds according to global characteristics determined by the transformer**.**

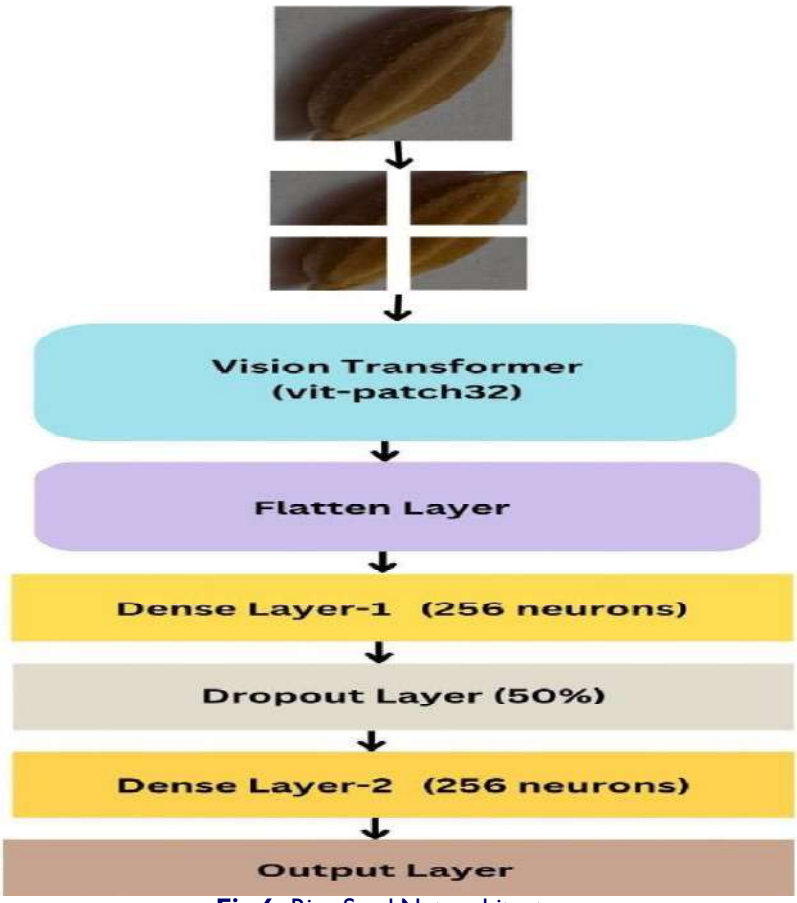

Fig 6- Rice Seed Net architecture

The change observed in the RiceSeed Net model, which uses the model to adapt to the rice seed, is shown inFigure. The model is designed to distinguish 13 different variables using the visual variation method asfollows:

Training: The RiceSeedNet model became a supervised process, training on photos recorded for low-qualitymeasurement. The goal of training is to reduce the input level by ensuring that the class prediction matches the actual text.

Inference: After training, the RiceSeedNet model distributes new, unseen photos of rice seeds. It does thisby creating photos from samples where the output of the distribution map represents the class list of riceseeds.

IMAGE CLASSIFICATION EMPLOYING VISION TRANSFORMERS

The architecture of RiceSeedNet is shown in Figure 6. These weights are optimized via backpropagation toreduce loss during training. Vision Transformer (ViT) divides each photo into blocks of 32 x 32 pixels, creating four blocks for each photo, each containing 512 points. ViT extracts features from these patches, which are then classified by a custom neural network (FCN). A thick layer [19]. The first two layers have 256 neurons each and have ReLU and L2 core normalizer functions. The releaseprocess between layers eliminates 50% of the connections to prevent collisions, and the second layer isfollowed by the first layer to ensure the safety of the product [20]. The last method uses the softmax activation function and has as many neurons as there are groups corresponding to the grain type. This layer displays the predicted values, showing the classes with the highest probability.

CONCLUSION:

The aim and moto of this study is to create map of local rice seeds and distinguish them using the custom-built visual transformation model RiceSeedNet. This study successfully used the RiceSeedNet model to identify 13 rice varietiesfrom the Indian state of Tamil Nadu with 97% accuracy. We also investigate the application of RiceSeedNet in rice identification, which shows99% accuracy of publicly available information on eight rice varieties. The solution provides great benefits to those involved in agriculture and enables the distribution of rice seeds and riceusing the best technology. Classification accuracy stands out, showing a 4% improvement in precision, accuracy andreturn measurements of 4% forgrain and 15% forseeds. Although more complex than the baseline network and InceptionV3, RiceSeed Net requires fewer computing resources for training due to its pre-training on extensive Photo Net data. The results were compared with other studies to evaluate the distribution capabilities of RiceSeedNet. Support agriculture. Going forward, this study canbe expanded by adding more photo data and increasing the number of seeds and grains. These improvements will benefit farmers and regulators by improving the identification process. However, one of themain limitations of this approach is that the preprocessing method sometimes does not segment all genes correctly,leading to the exclusionof negative samples. Additionally, the seed extraction algorithm may perform poorly in low light conditions, indicating areas for future improvement.

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