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Detecting Cereal Crop Pests Using Artificial Intelligence and Computer Vision: A Community Study.

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Abstract

Field crop production plays a vital role in the global economy. This necessitates the adoption of efficient and safe food production methods. Information technology is one of the tools available to achieve this goal. Among the available tools are computer vision, along with artificial intelligence algorithms, which have achieved significant results in pattern detection in images. This study aims to determine the applicability of computer vision in precision agriculture for the production of the five most productive cereals, which include maize, rice, wheat, soybeans, and barley. With different approaches to address aspects related to disease detection and cereal quality. It is possible to identify significant opportunities, such as leveraging GPUs (Graphics Processing Units), and advanced artificial intelligence techniques, such as DBN (Deep Belief Network), in developing robust computer vision methods applicable to cereal crop production.

Keywords: Cereal Crop Pests, Artificial Intelligence, Computer Vision, Community Study.

Introduction

The increased consumption of grains in recent years necessitates greater attention to efficient and sustainable agricultural practices to meet consumer demand. It is worth noting that image processing and computer vision applications have emerged due to decreasing equipment costs, increased computing power, and growing interest in methods for evaluating non-harmful foods [1].

The increased consumption of grains in recent years necessitates greater attention to efficient and sustainable agricultural practices to meet consumer demand. It is worth noting that image processing and computer vision applications have emerged due to decreasing equipment costs, increased computing power, and growing interest in methods for evaluating non-harmful foods [2].

Manual methods of grain assessment are challenging even for those trained in these tasks. One of the main difficulties is the training of these assessors. There are few facilities equipped to train people to the required standard. Another difficulty is the time required to conduct such assessments, which hinders rapid decision-making and large-scale evaluation. The use of computer vision, near-infrared spectroscopy, magnetic resonance spectroscopy, X-ray spectroscopy, and hyperspectral imaging are techniques that can be used to overcome these limitations [3].

These techniques, along with pattern recognition algorithms and automatic classification tools, were used, to address the challenge of monitoring and analyzing food quality. Machine learning algorithms were able to analyze massive amounts of data, regardless of complexity, quickly and accurately. It is essential to understand the individual characteristics of each method and the best scenario for its application. One of the key factors in the widespread adoption of machine learning was the extensive use of graphics processing units (GPUs). This has broadened its application across diverse fields such as industry, healthcare, and climate [4].

Furthermore, the emergence of the CUDA programming language and the introduction of dedicated hardware to facilitate parallel programming for these processors help developers build new applications. In this way, it is possible to achieve better solutions to a given problem in a shorter timeframe by using graphics processing units (GPUs) [5].

The combination of these three components—computer vision, machine learning, and high-performance computing—has proven promising in solving various problems in agriculture. The predictive capabilities made possible by deep learning, a technique that has gained prominence among other machine learning techniques, will have a disruptive impact on various sectors of traditional industry as well as agriculture [6].

These methods include detection, classification, and quantitative measurement. Techniques such as support vector machines, fuzzy logic, and neural networks are also evaluated. The work focused on the practical aspects of rice processing, such as measuring rice yield, milling degree, cleft determination, shape and size analysis, color analysis, variety classification, internal damage assessment, root estimation, and spike analysis. These were analyzed using computer vision systems applied in assessing food grain quality [7]. Among the applications analyzed, this study examines aspects, such as foreign material identification, insect infestation, microbial infection, and discolored grains. It also presents a survey of various image processing and machine learning techniques used to identify rice plant diseases based on images of infected rice. The survey was organized into two main parts. The first deals with image processing tasks, such as acquisition, preprocessing, segmentation, and feature extraction, while the second deals with machine learning tasks [8].

The current systematic study aims to utilize computer vision and artificial intelligence techniques for five major cereal crops. Five databases were used for analysis: leaf scanning for maize, rice, wheat, soybeans, and barley. The work was evaluated in three phases: identification, screening, and eligibility. In the identification phase, the results from the different databases were standardized to remove duplicate elements. In the eligibility phase, the results were evaluated, conclusions were drawn, and comparisons were made with other similar methods. The following information was obtained: a description of the image processing method, a description of the image classification method using artificial intelligence, and a description of the use of GPUs. In the identification phase, 1679 unique elements were obtained using metadata filtering when this feature was available. In the subsequent screening phase, the leaves were analyzed and selected for validation of the results.

Computer Vision:

Computer vision recognizes the methods and techniques by which artificial vision systems can be built and effectively employed in practical applications. This field of computer science encompasses the software, hardware, and imaging techniques necessary for these methods. Essentially, a computer vision system consists of the following stages: image acquisition and processing. It begins with the transmission of electronic signals from a sensor to a digital representation by a device such as a camera. Basically, two types of cameras can be used, distinguished by their scanning method: area or line. Conventional or area-scanning cameras create an image in each viewing cycle. In contrast, line-scanning cameras capture only one line of pixels at a time, to obtain two-dimensional images, it is necessary to move the object to be captured using a vector or to move the camera along a stationary object. The image quality obtained by a computer vision system is directly affected by the lighting used during the acquisition phase. In this way, every effort invested in using appropriate lighting will increase the system's performance and reliability, thus reducing software complexity [9].

Image processing: The tasks performed to process digital images include, for example, improving their quality, reducing noise, or correcting lighting issues. In addition, image analysis refers to the process of distinguishing areas of interest from other areas to extract information. It can be divided into low-level, intermediate-level, and high-level processing. Low-level processing, or preprocessing, includes grayscale adjustments, focus correction, contrast or sharpness enhancement, and noise reduction. These operations produce a new image and are used to improve image quality or to modify the position of the object of interest through geometric transformations. Meanwhile, intermediate-level operations include segmentation (dividing images into regions) and describing and classifying objects within the image. Segmenting an image results in a set of features or regions. Extracting the features that characterize these regions is essential for evaluating a range of properties of the area of interest. For example, the parameters of an ellipse allow you to determine the direction and size of a region. The bounding box allows you to calculate the height and width of the area of interest. Filters such as Sobel, Laplacian, and Laplacian of Gaussian can be used to identify areas where sudden changes in density occur in the image [10].

A Gabor filter is selective for elements in an image within a specific range of direction and frequency. Haar filters consist of adjacent rectangular areas that are balanced. The average value of the filter is zero and remains constant across changes in illumination. The purpose of edge detection is to produce a binary image where non-zero values indicate the presence of an edge in the image. Detectors may optionally also return other information such as scale and orientation relative to the edge. Some examples of edge detectors are Canny, Harris, and SIFT. SIFT detection is a method for identifying points of interest. It correlates scale and orientation information for each point detected [11].

Machine Learning:

Machine learning deals with the methods and techniques of computational applications that can modify or adapt their procedures to make them more accurate. Learning algorithms can be classified into the following categories: supervised learning, unsupervised learning, reinforcement learning, and evolutionary learning. Supervised learning algorithms start from a set of correct answers to generalize and respond correctly to all possible inputs. In contrast, unsupervised learning algorithms compare inputs to each other to identify similarities in order to classify them into categories. Reinforcement learning algorithms can be considered an intermediate stage between supervised and unsupervised learning. The algorithm is notified when it responds incorrectly to a question but not when it responds correctly [12].

The machine learning process consists of the following steps:

Data preparation and acquisition: The first step is to obtain suitable data that contains the characteristics to be considered in the learning process. Generally, learning algorithms require a large amount of data.

Selection of relevant characteristics: This involves identifying the most important characteristics of the problem to be addressed. • Algorithm selection: Determine the most suitable algorithm for addressing the problem under study.

Parameter selection: Some algorithms require parameter adjustments, which necessitate experimental selection.

Training: Given a set of inputs and an algorithm, training involves building the computational model that will be used to predict responses on new data.

Classification: The system needs to be evaluated for its accuracy on the trained data [13].

Support for Vector Machines (SVM):

An SVM (Support for Vector Machines) is a non-probability linear classifier that constructs the decision boundary with the greatest possible distance between the sample points. A classic SVM classifier can classify input points into two possible categories. In this way, it is possible to construct linear intervals even if they cannot be defined linearly in the original input space [14].

Neural Networks:

A neural network consists of nodes connected by directed links with associated weights that determine the strength and signal strength of the connection. Weights are the fundamental form of long-term storage in neural networks, and learning algorithms can typically update these weights. Input and output nodes are those that have connections to the outside world. Each node is independent of the others and can therefore perform its calculations only from its own input values and weights. A feed forward neural network has connections in only one direction and can be represented as a directed acyclic graph. This type of network represents a function and has no internal state except for the correlation weights. In contrast, a recurrent neural network feeds its outputs to the input nodes. In this way, the network forms a dynamic system that may or may not reach a steady state. Neural networks are organized in layers where each unit receives input only from the nodes of the next higher layer, with a hidden layer large enough to represent any continuous function with random accuracy. Using convolutional layers, subsampling layers, and fully connected layers. Initially, LeNet-5 was used to recognize handwritten numbers represented by 32 x 32 pixel two-dimensional images. The final layer contains the nodes that correspond to the probabilities of the original image belonging to one of the ten-digit categories [15].

Deep Learning:

Deep learning networks differ from traditional neural networks in that they have more nodes and more complex means of layer interrelation. They require significant computational power for training and have automatic parameter extraction. The four basic architectures used are: unsupervised networks, convolutional neural networks, recurrent neural networks, and iterative neural networks [16].

Computer Vision and Agriculture:

Cereal Diseases and Insect Infestations:

Cereal production is susceptible to a number of adverse factors associated with disease occurrence or pest and insect infestations. These factors can negatively impact crop development or reduce grain quality. Accurate detection and identification of diseases in cereal crops are crucial for effective management and ensuring productive and sustainable agriculture. Plant diseases are typically diagnosed visually and may be difficult to detect due to their complex and subjective nature. This work aims to propose AI-powered computer vision methods for automating plant disease detection. Automatic disease detection from images involves, among other factors, identifying the most distinctive characteristics for effective disease identification. Classification models can be used to categorize an image as healthy or diseased. It is also important to emphasize the variation in size and shape of these insects due to their species or developmental stage [17].

Detection of Pecan Disease in Rice Crops:

A method is proposed for classifying three-week-old seedlings into healthy and pecan-infected seedlings (Figure 1). Pecan disease is a rice disease primarily caused by the fungus *Fusarium fujikuroi*. When infected, plants exhibit changes in leaf color (becoming more yellow) or morphological abnormalities such as stem elongation, stunting, or a larger angle between the leaves and stem. Symptoms are highly complex and varied, as they differ according to plant resistance. This makes detection using computer vision challenging. The method presented uses plant images obtained using a scanner. Morphological and color characteristics are quantified, anatomical points of the plants are automatically identified, and the background is removed using a thresholding process at this stage [18].

Figure (1) Pecan disease in rice crops.

Efficiency of Computer Vision Methods for Detecting Leaf Diseases in Soybeans:

This study examines the ability to detect leaf diseases in soybeans (Figure 2) and the suitability of computer vision methods for detecting and classifying foliar diseases in soybean plants. The following descriptors were analyzed: WDH (Wavelet Decomposition Color Graph); BIC (Border/Interior Classification), which is a compact method for describing each pixel of an image as a border or interior; CCV (Color Coherence Vector), which allows for image comparison using color intensity; CDH (Color Difference Graph), which allows for encoding the visual appearance of images; LBP (Local Binary Pattern) descriptor, which is used to encode image texture information; and SSLBP (Square Symmetric Binary Pattern) descriptor, which encodes color and texture information. For classification, three models were analyzed: SVM, KNN (Nearest Neural Network), and PNN (Probabilistic Neural Network) [19].

Figure (2) Leaf diseases in soybeans

Detecting Aphids in Wheat:

Detecting aphids in wheat is crucial (Figure 3), as aphids are a pest that affects wheat crops. These insects feed on wheat bark sap, impacting its development and potentially transmitting a range of viral diseases. To monitor aphid populations and identify the species present in the field, the SMH (Supporting Vector Machine, Extremely Stable Regions, and Guided Gradient Schematic) method was proposed. This method combines the use of SVM, the MSER (Extremely Stable Regions) algorithm, and HOG (Gradual Gradient Schematic). Images used to train the classification model were acquired using conventional cameras positioned sideways to the plants during the elongation and budding stages. In the preprocessing step, filters were used to enhance contrast and reduce noise [20].

Figure (3) Aphids in wheat.

Local Descriptors for Soybean Disease Detection:

A method for the automated detection of diseases in soybeans was proposed. The method relies on local descriptors and the BOV (Bag of Values) method to encode input vectors for the classifier. After these leaves are collected in the field, they are scanned to obtain images. The use of local descriptors proves to be robust for blocking and does not require image segmentation. The method evaluated five different descriptors: SURF (Strong Accelerated Features), HOG, DSIFT (Dense Invariant to Scale Feature Transform), SIFT (Invariant to Scale Feature Transform), and PHOW (Visual Word Hierarchy Schemes). For classification, two categories, diseased and healthy, were defined in the SVM classifier [21].

Detection and Evaluation of Leaf Spot Severity in Wheat:

A computer vision method was proposed to automatically identify diseases causing leaf spot in rice (Figure 4). Images were acquired in the field, so background object processing was necessary. Due to noise in the images, it was necessary to first extract the target plant and then identify the disease patterns present in its leaves. To extract image features, the first operation performed was segmentation. To separate the target leaf from the background, we used MCW (Controlled Watershed) analysis. Once the target leaf was identified, t was necessary to obtain the disease characteristics that might be present in it. For this purpose, the SLIC (Simple Linear Iterative Clustering) algorithm was used [22].

Figure (4) Leaf spot in wheat.

Detection of *Sitophilus Granarius* in Stored Wheat:

Another pest that can cause significant damage to stored grain is Sitophilus granaries (Figure 5), also known as the "grain weevil." Detecting this type of infestation can be difficult and usually requires a specialist, increasing the time and cost of this type of assessment. Identifying the presence of this insect in the grain is suggested. The method involves using images obtained with a low-energy X-ray machine to identify internally damaged grains. The grains are arranged on X-ray plates to produce images. They are initially coded using a thresholding process. Traditional image analysis methods are used to determine certain characteristics such as grain circumference, area, and vertical and horizontal volume [23].

Figure (5) Detection of *Sitophilus Granarius* in stored wheat grains

Grain Quality:

Quality is a complex phenomenon influenced by numerous genetic and environmental factors. Traditional visual classification techniques used by the industry for wheat grains typically result in high error rates. In this sense, the use of machine learning techniques for image classification has been highlighted as a way to build more accurate and intelligent classification systems. However, the size, color, and texture of agricultural products are not determined by a single mathematical function, making the classification task challenging for computer vision systems. Computer vision systems offer an alternative to the manual inspection of grain samples. Visual inspection of these products is laborious and time-consuming. Operators often lose focus after hours of work due to fatigue, eye strain, or inadequate lighting. Therefore, automated classifiers can eliminate human error in the quality assessment process, making them a viable alternative to manual inspection [24, 25].

Wheat Grain Classification Using an Artificial Neural Network:

This computer vision system employs a simplified classification approach with a high accuracy index. The system aims to classify wheat grains according to their optical characteristics using an MLP (Massive Linear Perspective) artificial neural network. Images are acquired using a camera positioned perpendicular to the grains. These images are then converted to grayscale and binary using the Otsu method and segmented using a thresholding process. The size, color, and texture characteristics of each grain are captured to serve as inputs for the classification method. In this study, seven optical properties of the grains were selected: length, length-width ratio, greenness, blueness, greenness ratio, homogeneity, and entropy [26].

Identifying Fungal Colonies in Rice Using Computer Vision and Machine Learning Techniques:

This study investigated the feasibility of using computer vision in conjunction with traditional and deep learning machine learning techniques. It focused on detecting mold colonies in unhulled rice caused by microorganisms such as Aspergillus and Penicillium. The image acquisition system consisted of a camera, two LED strips, a camera mount, and a sample holder mounted on a black base. In the preprocessing step, the black background of the images was removed, and the images were standardized. The pixel center coordinates were calculated to eliminate interference from the plate used for sample deposition. Infected areas were identified using the color information of the image. For this purpose, two 512 × 512 pixel images were generated: one in grayscale and the other in RGB. A vector consisting of 64 color attributes was obtained from the 16-level histogram of the grayscale image and for each color channel in the RGB image. The areas containing the fungus in the sample images lacked uniform color, texture, and shape [27].

Shadow Measurement Method for Determining the Percentage of Filled Rice Grains:

As previously mentioned, rice grain filling is a crucial factor in determining grain yield. A method was developed to calculate the percentage of filled rice grains using shadows. The method utilizes four light sources to generate grain shadows in four directions. The difference between the shadows of filled and empty grains is evaluated using image analysis and an SVM classifier. The system was designed for use as an evaluation method. For this, a grain conveyor belt is used, allowing for analysis at a rate of 40 to 50 grains per second. In the preprocessing step, RGB images of the grains with shadows in the four directions are segmented using binary encoding [28].

Computer Vision Approach Using Two Cameras for Wheat Grain Identification:

High humidity before or during harvest can cause wheat grains to germinate prematurely. This condition leads to reduced grain quality. This computer vision system uses two cameras to separate and identify germinated wheat grains in a controlled environment. The system allows for classification into three categories: healthy grains, grains damaged by germination, and severely damaged grains due to germination. The image acquisition system consists of two cameras: one at the top and one at the bottom. The selection technique is used, and it is also important to avoid grain overlap to improve the accuracy of the classification method [29].

Rice Grain Classification Using BPNN and Wavelet Decomposition:

This study proposes using BPNN neural networks and wavelet decomposition to classify rice grains. The method utilizes two types of cameras to acquire images: The first is a 0.3-megapixel mobile phone camera, and the second is a conventional 12-megapixel camera. Images are acquired under natural lighting conditions in the morning to minimize shadow interference. Features are extracted from the images using three methods. The first method involves extracting 18 color features (RGB and HSI). The second and third methods employ GLCM and wavelet-based decomposition for each color channel (R, G, and B), respectively [30].

Classifying Wheat Grains Using DSIFT and SVM:

Evaluating the performance of using DSIFT technology in conjunction with an SVM classifier to classify wheat grains into 40 different types. SIFT is a computer vision algorithm for representing and identifying objects based on a set of localized features. The DSIFT algorithm is derived from the SIFT algorithm. The main difference between them is that DSIFT uses a sampling procedure to reduce the cost of SIFT. Initially, DSIFT extracts features from the image. Then, the k-means method is applied to this set of features. Finally, a BOW model is generated from the graph of the clustered features obtained in the previous step [31].

Rice Classification Using Fuzzy Inference:

Computer vision and fuzzy inference methods were used to develop a decision support system for classifying the quality of polished rice. The system uses two quality indicators to classify images captured in the computer vision system: milling degree (DOM) and percentage of broken grains (PBK). The approach captures images in RGB and cuts the rice grains using a threshold. The PBK measurement is obtained from the grain length in the images. The DOM measurement consists of assessing the grayscale. The intensity of the grayscale allows us to assess the amount of light passing through a sample of rice. The more bran remaining on the surface of the grains, the lower their transparency [32].

Grain Analysis of Milled Rice Using SVM:

Adverse factors such as harvesting immature grains and high moisture content can negatively impact grain quality. To improve the efficiency of the quality process, the percentage of grains should ideally be measured from the randomly distributed grains in the sample. The challenge of automatic detection lies in the presence of connected grains, which are always present in the sample, and manually separating them would significantly reduce process efficiency. An automated system for grain percentage analysis in rice is proposed. The algorithm handles grain separation automatically. After segmentation, the number of grains present in the image and specific grain information can be obtained [33].

Automated Wheat Purity Measurement System:

This computer vision system uses neural networks to automatically detect wheat purity. The experimental data consists of 52 inputs for color, morphology, and texture extracted from images. The algorithm combines ICA (Competitive Algorithm) and ANN to achieve two goals: To find the optimal set of parameters and create a robust classification system. The system was trained to classify wheat grains and impurities in the first system. Shadows are eliminated using RGB and HSI color spaces. Image processing is performed using a scanner [34].

Developing a Method Using Hyperspectral Imagery to Detect Fusarium-Damaged, Speckled, and Glassy Wheat Grains:

A method based on hyperspectral image classification was developed to identify three types of wheat (Triticum durum): Glassed, yellow berry, and Fusarium-damaged. Glassy grains are hard, transparent, and amber in color. Non-glassy grains are opaque and soft. Therefore, the glassy grade is an important quality factor for wheat because it improves the quality of the flour and the color of foods produced with it. In contrast, yellow berry or speckled grains negatively affect the quality of the flour produced due to their yellowish color and soft grain appearance. However, the industry tolerates the mixing of predetermined quantities of speckled and glassy grains. PCA is used for exploratory purposes to analyze the common characteristics of samples and their groups: Samples with similar spectra can be grouped into the same product category. However, PCA is an unsupervised method and cannot be used to build a predictive model like sample classification. In this sense, PLS-DA (Particle Least Squares Discriminatory Analysis) technology is used to identify a model capable of classifying the types of wheat used [35].

Study Discussion:

Generally, the analyzed methods use the same system: image acquisition, processing, and classification. However, each case requires the selection of appropriate algorithms, taking into account the individual characteristics of the problem being addressed. There is no default workflow that can be universally applied without modifications to its image discovery and processing strategy. Image segmentation also plays a crucial role in achieving the desired outcome. While it is easily applied to images acquired in controlled environments, this task is not as straightforward when images are obtained directly from the crop.

Machine learning algorithms are sensitive to the quantity and quality of the information used to train them. In some cases, when an algorithm "learns" about noise and excessive detail in our input set, it experiences overfitting, which negatively impacts the generalization ability of the built model. However, when data is insufficient, the model may fail to generalize when used with validation data. The evaluated works demonstrated different approaches to addressing this situation and correctly selecting attributes that ensure optimal method performance. A well-considered set of works employing algorithms for processing in the CPU and modules available in the MATLAB platform was implemented. Deep neural networks have become a viable solution for image classification thanks to the improved computing power of graphics processing units

(GPUs). Furthermore, CNNs have emerged as one of the most effective technologies for pattern recognition applications with large numbers of images. Interest in using computer vision and artificial intelligence is evident, for example, in the automated detection and identification of diseases, the classification of microorganisms, and the detection of insects in stored grains using deep learning.

Study Conclusion:

Computer vision systems are already widely used in various sectors of agricultural and industrial food production. They can be used in systems for classifying oranges, almonds, potatoes, lemons, wheat, corn, rice, and soybeans. Their use is justified by the benefits gained. Using such systems provides simple and objective sample analysis, resulting in accurate descriptive data. Through these systems, it is possible to automate labor-intensive tasks in a harmless way and generate sufficient data for future analysis. It has been identified that there are gaps that need to be filled with the development of smart devices that use computer vision and artificial intelligence to automate tasks in this field, as well as their integration with agricultural machinery and drones. Expanding the use of graphics processing units and advanced artificial intelligence technologies also presents promising alternatives for future work. For example, wheat, oat, and barley varieties can benefit from a computer system that aims to reduce the complexity and costs of classifying gluten-containing grains from images. We intend for this survey to present diverse applications and techniques of machine learning, image processing, and video to solve agricultural problems. Studying the introduction that has been proposed to solve it, along with new developments in computer vision and artificial intelligence, could lead to new solutions for agriculture that achieve gains in production, quality, and food security.

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الكشف عن أفات محاصيل الحبوب باستخدام تقنية الذكاء الاصطناعي والرؤية الحاسوبية: دراسة مجتمعية

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الخلاصة:
يلعب إنتاج المحاصيل الحقلية دورًا مهمًا في الاقتصاد العالمي. ويتطلب ذلك اتباع طرق فعالة وآمنة لإنتاج الغذاء. تعد تكنولوجيا المعلومات إحدى الأدوات لتحقيق هذه الغاية. من بين الأدوات المتاحة هي الرؤية الحاسوبية جنبًا إلى جنب مع خوارزميات الذكاء الاصطناعي التي حققت نتائج مهمة في اكتشاف الأنماط في الصور. تهدف هذه الدراسة إلى تحديد قابلية تطبيق الرؤية الحاسوبية في الزراعة الدقيقة لإنتاج الحبوب الخمسة الأكثر إنتاجًا والتي تشمل الذرة والرز والقمح وفول الصويا والشعير. مع مناهج مختلفة لعلاج الجوانب المتعلقة باكتشاف الأمراض وجودة الحبوب. من الممكن تحديد فرص كبيرة مثل استغلال (GPU وحدة معالجة الرسومات) وتقنيات الذكاء الاصطناعي المتقدمة مثل (DBN شبكة الاعتقاد العميق) في بناء أساليب قوية للرؤية الحاسوبية تطبق على انتاج محاصيل الحبوب.

كلمات افتتاحية: آفات محاصيل الحبوب، الذكاء الاصطناعي، رؤية الحاسوب، دراسة مجتمعية.