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UTILIZATION OF COMPUTER VISION AND MACHINE LEARNING FOR APPLIED ENGINEERING: DATA ANALYSIS AND RECOGNITION

Purpose. The primary purpose of this research article is to develop a ML model for applied engineering for varied actions, such as identifying sunflower seeds from other seed types and adjusting the screw press parameters accordingly for optimal oil extraction. Additionally, it aims to predict noise propagation and implement measures for noise reduction in relevant engineering applications.

Methodology. The research methodology involved analyzing scientific sources, experimental data, modeling, and machine learning. The ML model was trained using the Edge Impulse platform with a dataset of seed images, annotated for focus. After iterative training, validation, and testing, the model was embedded into an Arduino controller for real-time seed identification and automatic screw press operation regulation.

Findings. This article introduces an innovative applied engineering approach aimed at revolutionizing the seed oil extraction process through the automation of screw press operations using Machine Learning (ML) and Computer Vision (CV). Key findings include the successful differentiation between sunflower and pumpkin seeds and precise adjustment of screw press settings based on seed type identification. ML is also utilized to detect an empty seed feeder and halt press operations automatically, preventing equipment damage and ensuring efficiency. These results pave the way for enhanced automation and precision in seed oil extraction processes.

Originality. The application of ML and CV in seed oil extraction and screw press operation, as presented, underscores the transformative potential of these technologies in agricultural processes.

Practical value. Incorporating computer vision and machine learning into applied engineering streamlines processes, reduces errors, and enhances efficiency. This integration optimizes resource utilization, enables real-time decision-making, and boosts productivity across various engineering applications.

Keywords: artificial intelligence; image recognition; Arduino; screw press; seeds; advanced engineering.

Introduction. The dynamic evolving in advanced engineering, particularly within agricultural domains, have sparked innovative approaches leveraging cutting-edge technologies such as Computer Vision (CV) and Machine Learning (ML) to enhance and optimize processes, reshaping the sector. A prime example of this technological fusion is the evolution of conventional seed oil extraction methods, notably through the utilization of screw press technology.

Leveraging Computer Vision (CV) and Machine Learning (ML), the conventional method of seed oil extraction via a screw press involves numerous manual tasks, posing challenges regarding efficiency, time, and error rates. Given the varied characteristics of seeds and their unique extraction needs, manually configuring the screw press settings for each seed type becomes labor-intensive. This not only hampers process speed but also risks yield reduction due to potential inaccuracies. Thus, the creation of an automated system to streamline and optimize this process could have substantial implications for the agricultural sector.

As advanced engineering techniques progress, the integration of these evolment into screw press operations to address existing challenges becomes increasingly relevant and feasible. Utilizing Machine Learning (ML) and Computer Vision (CV) offers a promising solution to automate seed identification and adjust machine parameters accordingly. This integration holds the potential to enhance efficiency, decrease processing times, and boost yield.

Recent studies have begun to explore the potential of incorporating AI, ML and CV in various agricultural practices. The article [1] reviews the application of advanced technologies like computer vision and deep learning in seed testing and identification. It discusses the possible benefits and

limitations of these methods and acknowledges challenges associated with their implementation and suggests optimization strategies for these systems. Article [2] explores the use of computer image analysis and machine learning algorithms, such as deep learning, SVM and random forest, to extract morphological data from seeds and classify species of aquatic plants.

The study [3] presents a computer vision tool named DiSCount (Digital Striga Counter) to automate the quantification of total and germinated Striga seeds. In research [4] authors developed a computer vision system using a regular colour camera under controlled lighting and investigated that the highest accuracy (95%) can be achieved using the GoogleNet algorithm. In research [5] authors utilized computer vision to classify canola varieties, using images captured by a digital camera in natural light. They achieved impressive accuracy rates – up to 98%. This work [6] introduces an affordable and efficient system for measuring seed volume, crucial for seed breeding programs.

In work [7] authors applied four traditional classification algorithms and trained the dataset using a deep learning method, VGG19. The paper [8] reviews how AI is transforming various agricultural activities. Studies [9, 10] aim to create a food detection system based on Arduino to alert users of food spoilage. However, the focus on automating and optimizing the screw press operation specifically, using these technologies remains an under-explored area. This articles [11, 12] seeks to address that gap by presenting a novel technological solution that leverages ML and CV for seed type recognition and automatic parameter adjustment in a screw press operation.

Setting the research task. The primary task of this article resides in leveraging Machine Learning (ML) and Computer Vision (CV) to differentiate sunflower seeds from other seed types efficiently and effectively. The ability of an automated system to accurately identify a particular seed type is integral in determining the optimal settings required for a screw press operation.

To concretize our research path, we outline the following main objectives:

1. Training Machine Learning (ML) algorithms to accurately recognize and differentiate sunflower seeds from other seed types using Computer Vision (CV), focusing on the unique visual aspects of sunflower seeds.
2. Leveraging the seed identification process to automatically optimize the operation of the screw press. This involves determining and adjusting the screw press parameters for optimal oil extraction based on the identified seed type.
3. Utilizing ML to recognize when the seed hopper is empty and automatically pause the operation of the screw press, preventing possible equipment damage and promoting efficient use.

In accomplishing these goals, this article aims to cover the crucial yet under-explored segment of infusing ML and CV into the field of oilseed extraction, bridging the existing gap and providing a robust solution for the identified challenges.

Results. The Edge Impulse platform was leveraged in this study for its versatile and user-friendly features, allowing for seamless development and implementation of machine learning models even with modest hardware. The platform not only provides an effective training environment for the model but also supports the deployment of this model into a real-time system.

A diverse dataset of sunflower and pumpkin seeds in various states (shelled and unshelled) was collected for use in convolutional neural networks (CNNs) and autoencoders. Images were taken under different lighting conditions for better role modelling. Uploaded to Edge Impulse, this dataset facilitates further analysis and generative adversarial networks (GANs) model development, contributing to seed identification technology advancements.

Furthermore, to make the data analysis more efficient and focused, a technique known as bounding box annotation was employed. This involved marking an area of interest – the seed – in each image, which allows the platform to focus exclusively on the defined area during model training.

A convolutional neural network (CNN) comprises convolutional layers for feature extraction, followed by activation functions like ReLU for non-linearity. Pooling layers down-sample feature

maps, while fully connected layers learn high-level features for classification/regression. The output layer produces final predictions. Through training on labeled data, CNNs learn to extract features and make accurate predictions.

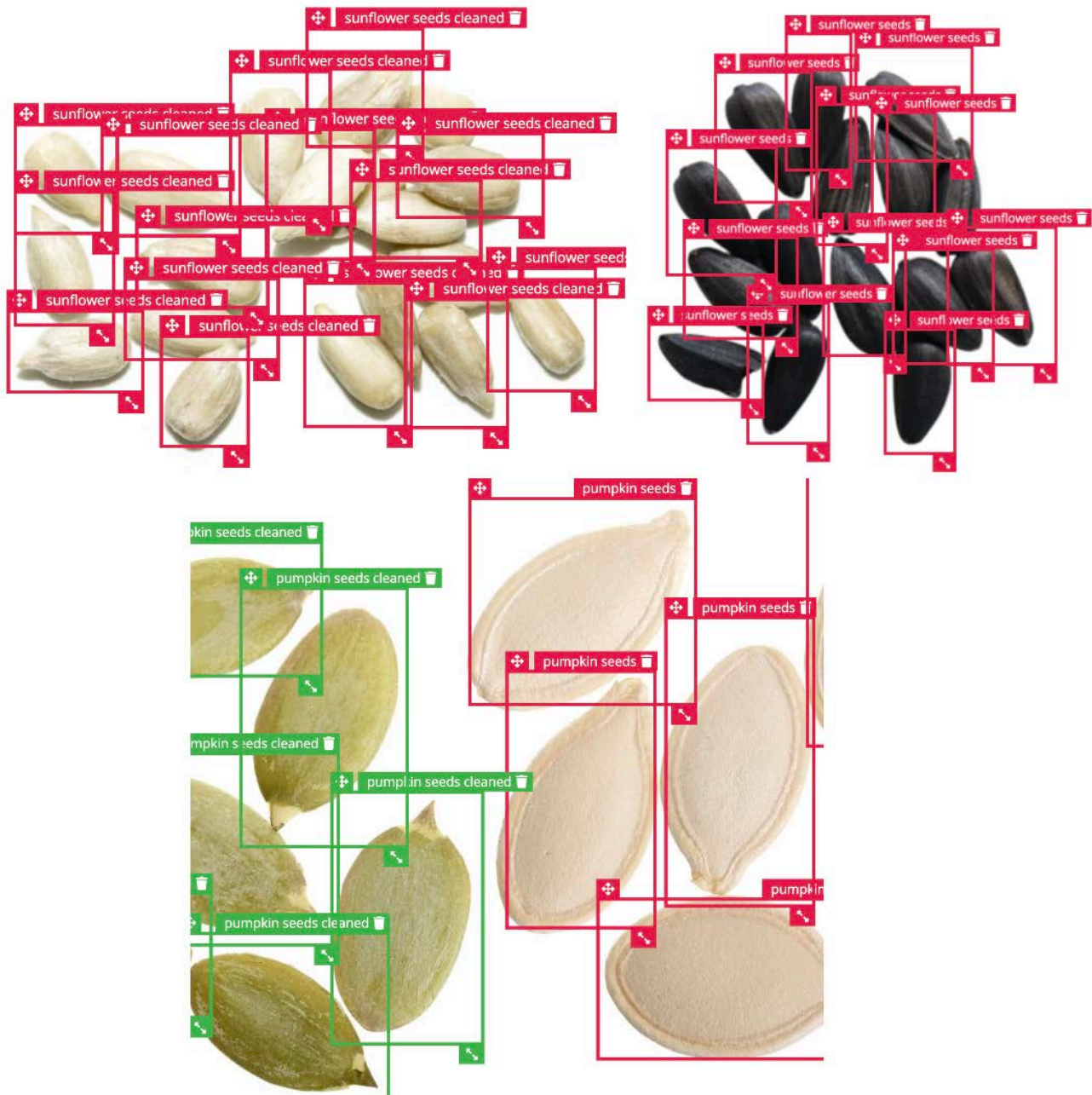


Fig. 1. Seeds type detection

Using annotated images, the system trained the model to distinguish sunflower seeds, pumpkin seeds, and an empty feeder. Through iterative cycles of supervised learning [13], validation [14], and testing [15], the model's accuracy and performance improved. This meticulous training enhances both performance and scientific understanding of feature recognition in machine learning algorithms.

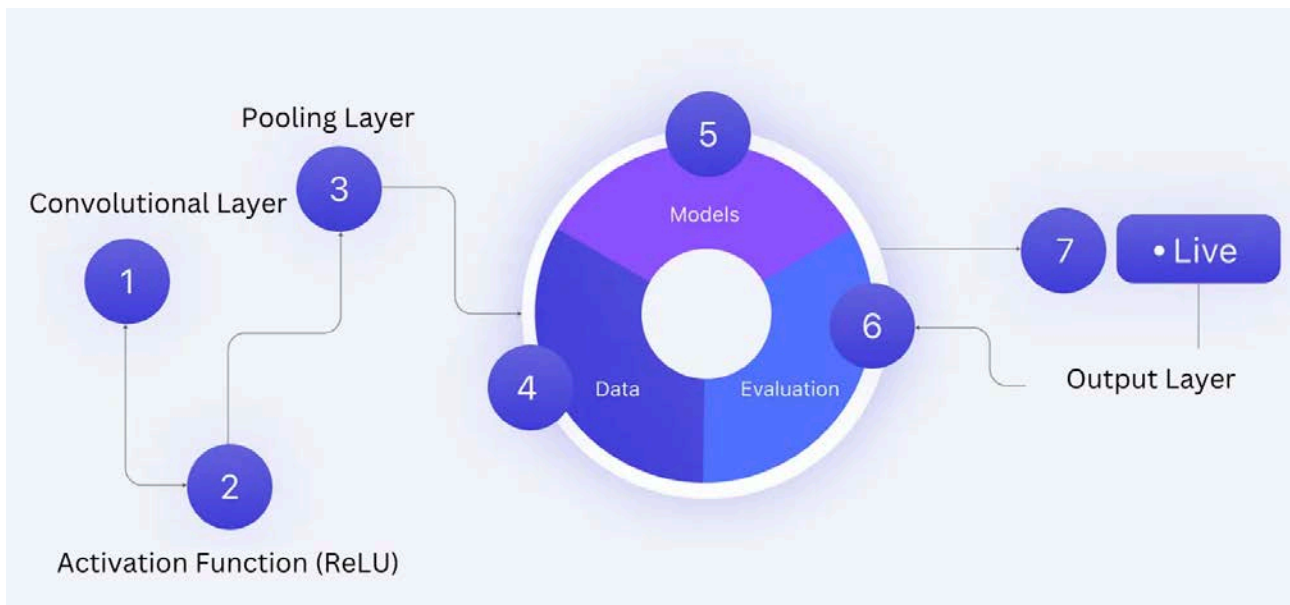


Fig. 2. A convolutional neural network for images analysis

Training set

Data in training set

23 items

Classes

4 (pumpkin seeds, pumpkin seeds cleaned, sunflower seeds, sunflower seeds cleaned)

Generating features...

Feature generation output

Cancel

🗑️ (0)

```
Job started
Fetching info for data items...
Fetching info for data items OK

Scheduling job in cluster...
Container image pulled!
Job started
Creating windows from files...
[ 1/23] Creating windows from files...
[23/23] Creating windows from files...
Creating windows from files OK

Created 24 windows with 330 objects: pumpkin seeds: 113, pumpkin seeds cleaned: 49, sunflower
seeds: 111, sunflower seeds cleaned: 57
```

Fig. 3. Training process

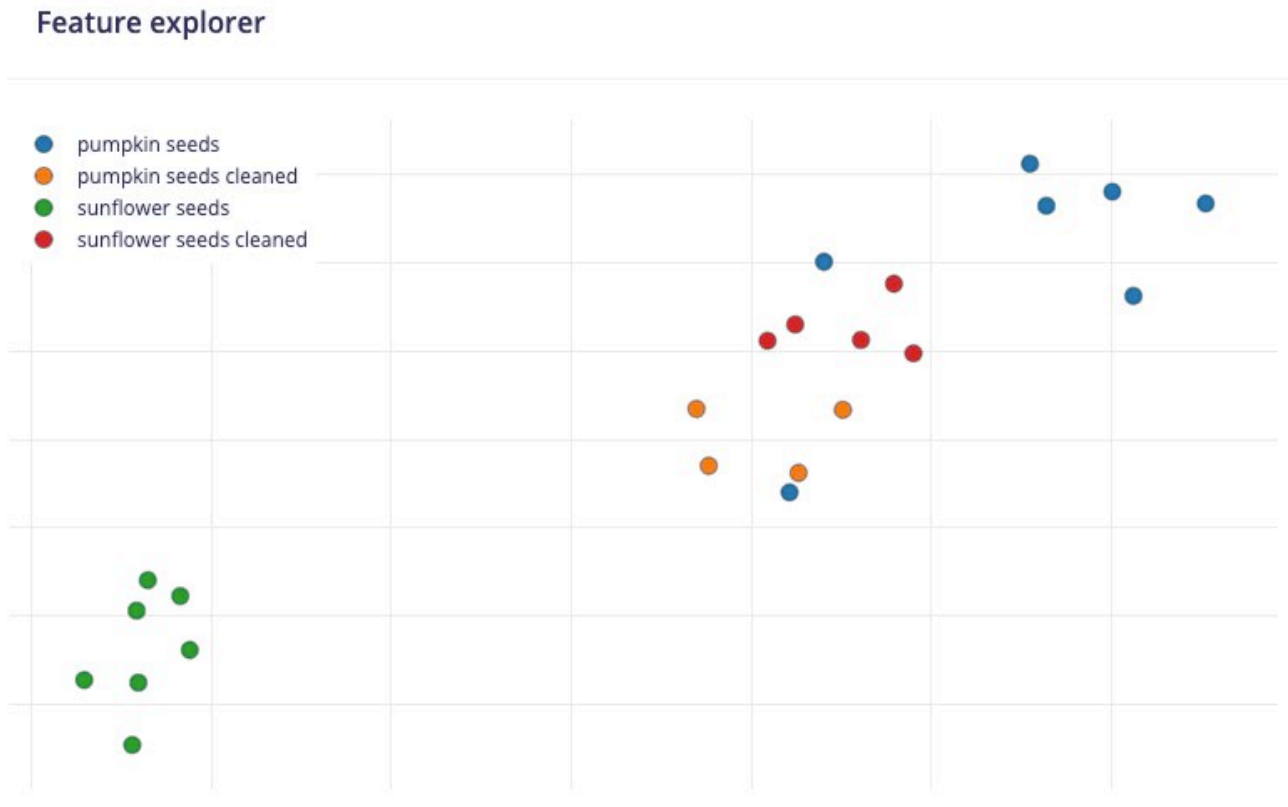


Fig. 4. Plot of all the data in dataset

In a live operational setting, a camera will be installed on the feeder to continuously monitor incoming seeds, integrated into an Arduino controller. Utilizing a model trained and validated on similar images, the system will identify seed types in real-time and classify them accordingly. With the seed classifier, the screw press can automatically adjust to optimal working parameters, such as height and temperature, specific to the identified seed type. Implementing this screw press model setup reduces human errors and addresses obstacles through automated adjustments per identified object. Moreover, the model's versatility allows it to be trained for various applied engineering challenges.

In the screw press operation for sunflower seeds, key parameters affecting oil extraction include height, temperature, and pressing speed. Maintaining the pressing temperature between 105–110 degrees Celsius ensures a high oil yield and preserves nutritional quality. Optimal speed is crucial for efficient seed crushing without overheating the oil. Additionally, the gap between the barrel and screw shaft must be precise to facilitate smooth seed movement. A too-wide gap reduces pressure and oil yield, while a too-narrow gap risks equipment damage.

Using ML, the system can adapt, learn, and improve over time, making the process more efficient. Meanwhile, CV will assist by accurately classifying different types of seeds, helping the system understand what type of seed it is dealing with and how to adjust the settings on the screw press accordingly.

Conclusion. In this research article, we've demonstrated the integration of Machine Learning (ML) and Computer Vision (CV) in optimizing the screw press operation. Firstly, with the use of the Edge Impulse platform, we successfully developed and trained an ML model to differentiate sunflower seeds from other seed types using distinctive visual characteristics. This was made possible through utilizing a robust dataset and the application of bounding box annotation for focused image

analysis. We effectively leveraged this seed identification process to optimize the screw press operation. By determining the seed type, the ML model was able to automatically adjust the parameters of the screw press for optimal oil extraction.

ML model was also trained to detect an empty seed hopper, allowing the system to automatically halt the screw press operation, preventing possible damage to the equipment and ensuring efficient use of resources.

These successful results solidify this ML-based method's potential in enhancing efficiency and precision in the oil extraction industry. The integration of such smart technologies into agricultural practices is a revolutionary step that opens the door for further advancements in automating and optimizing manual processes, thereby paving the way for the future of smart agriculture.

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ВИКОРИСТАННЯ КОМП'ЮТЕРНОГО ЗОРУ ТА МАШИННОГО НАВЧАННЯ ДЛЯ ПРИКЛАДНОЇ ІНЖЕНЕРІЇ: АНАЛІЗ ТА РОЗПІЗНАВАННЯ ДАНИХ

Мета. Розробка моделі машинного навчання для застосування прикладної інженерії для широкого спектру дій, як ідентифікація насіння соняшника серед інших видів насіння та налаштування параметрів шнекового преса відповідно для оптимального видобутку олії. Крім того, вона спрямована на широкий спектр аналізу, для прикладу передбачення моделі для визначення та зменшення шуму.

Методика. Аналіз наукових джерел, експериментальних даних, моделювання та машинне навчання. Модель машинного навчання була навчена за допомогою платформи Edge Impulse за допомогою набору зображень насіння, анотованих для фокусу. Після ітеративного навчання, перевірки та тестування модель була вбудована в контролер Arduino для ідентифікації насіння в реальному часі та автоматичного регулювання роботи шнекового преса.

Результати. Ця наукова стаття пропонує альтернативний експериментальний підхід в прикладній інженерії, спрямований на процес видобутку насіння для отримання олії за допомогою автоматизації операцій шнекового преса з використанням машинного навчання (ML) та комп'ютерного зору (CV). Ключові результати включають успішне розрізнення насіння соняшника та гарбуза та точне налаштування параметрів шнекового преса на основі ідентифікації типу насіння. ML також використовується для виявлення пухляка та автоматичної зупинки роботи преса, що запобігає пошкодженню обладнання та забезпечує ефективність. Ці результати відкривають шлях до покращення автоматизації та точності в процесах видобутку насіння для отримання олії.

Наукова новизна. Представлене застосування ML і CV в контексті екстракції олії з насіння за допомогою шнекового преса практичним експериментальним методом підкреслює потенціал використання технологій у прикладній інженерії, зокрема оптимізації сільськогосподарських процесів.

Практична значимість. Стаття виявляє практичну користь на основі експериментальних даних, що полягають в автоматичній оптимізації процесу видобування олії, зменшенню кількості ручної роботи, та збільшенню продуктивності в даній індустрії виготовлення олії, а також застосування цих методів у галузі прикладної інженерії. Це дослідження є кроком у напрямку автоматизованого майбутнього, в якому передові технології допомагатимуть реалізувати прогресивні, ефективні та сталі підходи галузі агрокультури.

Ключові слова: штучний інтелект; розпізнавання зображень; Arduino; шнековий прес; насіння; прикладна інженерія.