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Aboul Ella Hassanien
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The 8th International Conference on Advanced Machine Learning and Technologies and Applications (AMLTA2022)

Springer

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Preface

This volume constitutes the refereed proceedings of the 8th International Conference on Advanced Machine Learning Technologies and Applications, AMLTA2022, held in Port Said University, Port Fouad, Egypt, during May 5–7, 2022. The 8th edition of AMLTA will be organized by the Scientific Research Group in Egypt (SRGE), Egypt, collaborating with Port Said University, Egypt, and VSB-Technical University of Ostrava, Czech Republic. AMLTA series aims to become the premier international conference for an in-depth discussion on the most up-to-date and innovative ideas, research projects, and practices in the field of machine learning technologies and their applications. The accepted papers cover current research on advanced machine learning technology, including deep learning technology, sentiment analysis, cyber-physical system, IoT, and smart cities informatics and AI against COVID-19, data mining, power and control systems, business intelligence, social media, and digital transformation, and smart systems.

We want to emphasize that the success of AMLTA2022 would not have been possible without the support of many committed volunteers who generously contributed their time, expertise, and resources toward making the conference an unqualified success. We express our sincere thanks to the plenary and tutorial speakers, workshop special session chairs, and international program committee members for helping us to formulate a rich technical program. We want to extend our sincere appreciation for the outstanding work contributed over many months by the Organizing Committee: local organization chair and publicity chair. We also wish to express our appreciation to the SRGE members for their assistance. Finally, thanks to the Springer team for their support in all stages of the proceedings' production.

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Deep Learning and Applications

Plant Leaf Diseases Detection and Identification Using Deep Learning Model

Dang Huu Chau[1], Duong Chan Tran[1], Hao Nhat Vo[1], Tai Thanh Do[1], Trong Huu Nguyen[1], Bao Quoc Nguyen[1], Narayan C. Debnath[2], and Vinh Dinh Nguyen[1](✉)

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Abstract. In agriculture, leaf diseases often appear in changing weather conditions. Changing weather conditions can be very rainy or very hot or very humid. These factors make plants susceptible to bacterial, fungal, and viral infections. This research investigates three common diseases on apple trees, such as black rot, fish scale disease, snow apple rust. We use the deep learning method-based Yolo-v5 model along with the proposed stable information based on auto-encoder to train a Plant-Village dataset with 5740 images; The proposed system uses Google Colab for training phases. The data set is divided into three parts: training, validation, and test. We used 70% dataset (4018 images) for training, used 20% dataset (1148) for performing the validation step, and 10% dataset (574 images) for a testing phase. After training, we obtained the result of 81.28% in terms of the detection rate and 91.93% in terms of the classification rate by using the Plant-Village dataset.

Keywords: Leaf diseases detection · Deep learning · Leaf diseases classification

1 Introduction

The establishment of The World Trade Organization (WTO) in 1995 and the Sanitary and Phytosanitary Measures Agreement (SPS Agreement)[1] facilitates the liberalization of commercialization generally and the commercialization of agricultural products particularly. Those have boosted trade, reduced trade barriers, and created energetic conditions for development. However, in Agricultural Countries, Newly Industrializing Countries (NICs), the SPS Agreement seems to have been consigned to oblivion. As the consequence, it causes some unfavorable

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conditions for commercialization and leads not being too invested and focused production process. The difficulties of finding data sets on plant diseases; with using machine learning methods to recognize, classify, predict, analyze risks and provide solutions become not as easy as anything.

There are a vast majority of diseases and pests that agricultural products have to deal with currently. In apple trees, there are some typical diseases such as white root-rot, fire blight, black rot, fish scale disease, snow apple rust, bitter rot disease, blue mold disease, mosaic disease, etc. Those diseases and pests are alarming and threatening since they always tend to evolve to adapt to and resist human pests' control measures. A new disease or a new fungus could drastically reduce the quality of a crop, or even destroy the whole crop if an immediate solution is not found. Beyond the cause agriculture has not been focused on development, another reason is almost farmers might only rely on experience to diagnose disease; therefore, they do not have a method of prevention or treatment methodically, leading to reducing the quality of agricultural products. Furthermore, the difference is pretty enormous using pesticide residues compared to the standards of the consuming countries is also another cause. To sum up, Those are challenges for developing countries in consuming agricultural products, because of the fastidious and strict requirements of the "big brothers" in the economy on the quality of imported agricultural products [2,16].

In Vietnam, agriculture plays a very important role that is an activity for millions of farmers. Thus, it is necessary to investigate methods that can help a farmer to deal with many available plant diseases in agriculture. There are many methods that have been investigated to detect and classify plant diseases as discussed in Table 1. Deep learning has been applied to solve various problem domains from texture classification to autonomous cars. However, it is just a few studies of deep learning to improve the performance of an agriculture-based application. This research aims to investigate an efficient deep learning model to effectively detect and classify plant leaf diseases to help the farmer easy to recognize the plant diseases and find their corresponding meditation. The proposed system aims to use the deep learning-based Yolo-v5 method [13] and the proposed stable feature-base auto-encoder to detect and classify plant leaf diseases. Experimental results proved that our proposed system provided a good accuracy when detecting and classifying plant leaf disease with 81.28% in terms of the detection rate and 91.93% in terms of the classification rate. We organized our research paper as follows: the existing research in the field are presented in Sect. 2. Section 3 describes the proposed method in detail. We verify the results of our proposed system in Sect. 4. Discussion and limitations are discussed in Sect. 5.

2 Related Works

When the plant is infected it is really difficult for farmers to find out which disease in order to select an appropriate method for curing the plant. To help the farmer sort out current problems, many plant disease detection and classification algorithms have been proposed as shown in Table 1. Sardogan et al. used vector quantization and convolutional neural network (CNN) techniques to detect and classify the disease tomato leaf [3]. Gadade et al. introduced a segmentation method for detecting segmentation of infected regions [4]. Recently, Luna et al. introduce a new algorithm, name Diamante Max to detect and classify the tomato leaf disease [5]. Their method is designed to detect various kinds of leaf disease, such as phoma rot, leaf miner, and target spot. More recently, Le et al. found that ResNet with 18 layers is suitable for detecting and classifying apple leaf disease [6]. After investigating the existing methods of detecting and classifying plant diseases, we found that the existing plant leaf-detection-based approach is still not satisfactory for the industrial application in terms of processing time and accuracy. Therefore, in this research, we will investigate Yolo-v5 [13] to develop a robust method for detecting and classifying three kinds of plant diseases: apple-scab disease, black-rot, and Cedar-apple.

Table 1. A survey of existing plant leaf diseases detection

Authors	Algorithm	Descriptions	Orther
Sardogan, M. [3]	LVQ	Take the input image, process and classify it according to certain categories	Use RGB convolution for dataset and reLU, max pooling for output
Gadade, H. D. [4]	LVQ	Fully automatic disease analysis, detection and measurement	Using a classification approach to detect diseases, classifying diseases use color-based thresholding and calculate area percentage to measure severity
de Luna, R. G. [5]	Auto-encoder	Learn efficient data encodings in an unsupervised way	Use Alexnet and RCNN to speed up disease detection
Li, X. [6]	OTSU	Analyze foreground and background to locate disease	Use SVM, ResNet, VGG to compare and improve results after each execution
Jiang, D. [7]	k-Means	Split the data into multiple clusters, each cluster corresponds to a disease	Using Resnet-50 model to improve analysis and training
Indumathi, R. [8]	Random Forest	Randomize disease data to build Decision Tree and synthesize results	Image data is preprocessed and uses the K-Medoid system to find diseased areas
Chakraborty, S. [9]	Otsu thresholding	Process and separate the diseased part, then compare it with the original image in the dataset	Use histogram to process and balance images to increase accuracy
Kumar, S. [10]	K-means	Separating diseased objects on leaves, dividing into clusters and conducting analysis	Use SVM, GLCM to classify different diseases in dataset
Mekha*, P. [11]	Random forest	Accurate identification of segmentation information classification and statistics based on huge data sets	Compare the accuracy of algorithms to choose the right algorithm
Reddy, T. V. [12]	Cascade Inception	Disease identification through comparison with the previously trained dataset	Optimize the training process by using AlexNet and GoogLeNet

3 Proposed Method

Existing plant leaf disease detection systems fail to obtain both fast processing time and high accuracy for a commercial product. Therefore, in this research, we aim to apply Yolo-v5 architecture [13] to develop a robust plant leaf disease detection and classification for three types of disease: apple-scab disease, black-rot, and Cedar-apple. In this research, first, we study the benefit of auto-encoder [15]. Second, we introduce a robust feature-based auto-encoder method to encode and extract robust information/texture for training and detecting plant leaf disease. Figure 1 shows the proposed model by using Yolo-v5-architecture and Auto-encoder architecture. Our proposed robust feature T is calculated as follows:

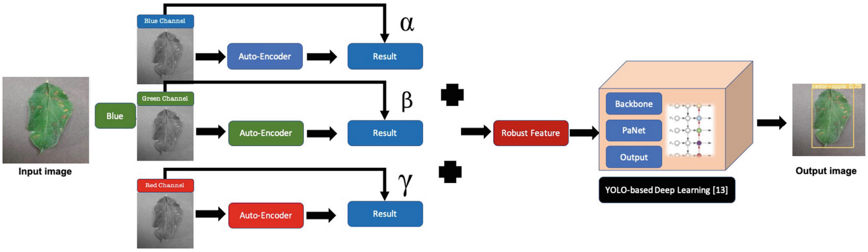


Fig. 1. The proposed system using Yolo-v5 [13] architecture to detect and classify leaf disease

$$\begin{aligned}
&AE^{c}_{(n)}\left(I\right) = \frac{1}{1+e^{-\left(W_c^{(n)} * AE^{c}_{n-1}(I) + b_c^{(n)}\right)}}\\
&\mathrm{O}_{blue}\left(I_{blue}\right) = \alpha_{blue} AE^{c}_{(n)}\left(I\right) + \left(1-\alpha_{blue}\right) I_{blue}\\
&\mathrm{O}_{green}\left(I_{green}\right) = \alpha_{green} AE^{green}_{(n)}\left(I\right) + \left(1-\alpha_{green}\right) I_{green}\\
&\mathrm{O}_{red}\left(I_{green}\right) = \alpha_{red} AE^{red}_{(n)}\left(I\right) + \left(1-\alpha_{red}\right) I_{red}\\
&\mathrm{T} = \beta_{blue} \times \mathrm{O}_{blue}\left(I_{blue}\right) + \beta_{green} \times \mathrm{O}_{blue}\left(I_{blue}\right)\\
&+ \left(1-\beta_{blue}-\beta_{green}\right) \times \mathrm{O}_{red}\left(I_{red}\right)
\end{aligned} \tag{1}$$

where $\mathrm{O}_{blue}\left(I_{blue}\right)$, $\mathrm{O}_{green}\left(I_{green}\right)$, and $\mathrm{O}_{red}\left(I_{red}\right)$ are the result after applying auto-encode $AE^{c}_{(n)}\left(I\right)$ on the image channel c.

4 Experimental Results

We use a total of 5740 images of PlantVillage dataset [14]. After the process of assigning labels to 3 diseases of apple trees: black-rot, apple-scab, cedar-apple. Next, we split the dataset into three parts: training Set (4,018 images), validation Set (1148 images), and testing Set (574 images). To make the training process go smoothly and save time, we took advantage of Google Colab's GPU. With equivalent epochs of 99, the batch of 64, the model we used is Yolo-v5 and finally got the result as Fig. 2. The dataset is organized in a balance way to help the proposed system obtain the best result in training.

First, assign labels to the images so that the diseased part of the leaves is shown specifically, the images are taken from many different light environments to increase accuracy when applied in practice. Then conduct training with Yolo-v5 model, will conduct training with the number of epochs pre-installed, with 5740 images, 1 epoch takes 1 min 38 s for ColabPro. And about 2 min 45 s for Colab free version. It also depends on the user's internet speed. After obtaining the training results, we proceed to use 10% of the dataset used for testing (574 images was not trained), the results obtained are about 81.28% in term of the detection rate, and 91.93% in term of the classification rate. While the original Yolo [13] achieved the detection rate of 78.85% and classification rate of 89.95%.

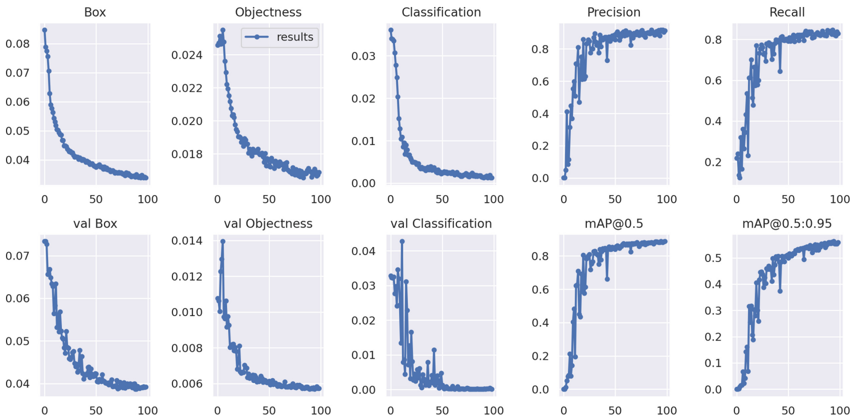
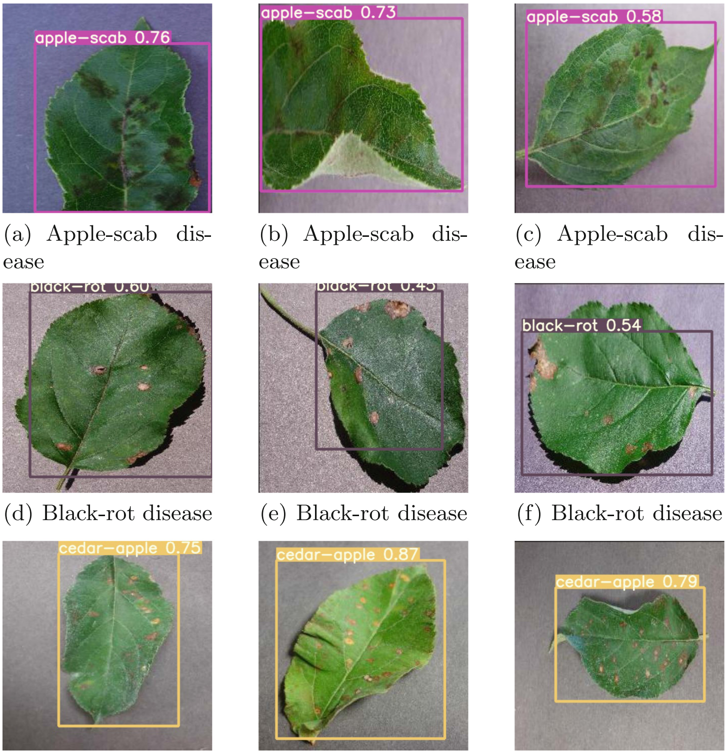


Fig. 2. Result after training on Yolo-v5

After the training process, the results obtained as shown in Fig. 3 include three diseases: apple scale disease, black rot disease, and cedar disease. The locations with translation are delimited by the Ground Truth bounding box. The Ground Truth bounding box is the contour that we assign labels to the object using the Roboflow website. Roboflow provides a lot of utilities that are especially suitable for data set management. To be able to conduct accuracy checks, we use IoU (Intersection over Union) - an evaluation metric used to measure the accuracy of object detection on a particular data set). If the IoU ratio between the Truth bounding box and the Prediction bounding box is greater than or equal to 0.5, the object is correctly recognized (True positive: TN). Conversely, if the IoU ratio is less than 0.5, the object is falsely identified (False positive: FP). And if the object is not recognized then it is False negative: FN.



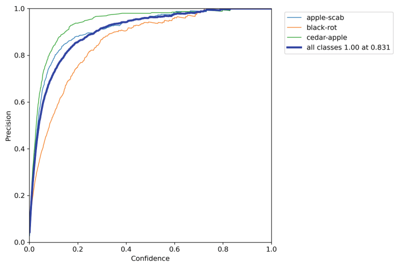
(a) Apple-scab disease (b) Apple-scab disease (c) Apple-scab disease

(d) Black-rot disease (e) Black-rot disease (f) Black-rot disease

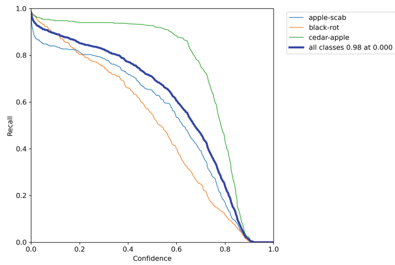
(g) Cedar-Apple disease (h) Cedar-Apple disease (i) Cedar-Apple disease

Fig. 3. Training results of 3 types of leaf diseases

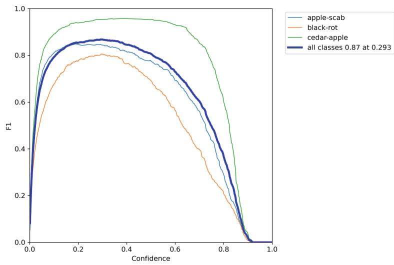
Figure 4 is a graph showing Precision, Recall, and F1-score. Precision is reaching 0.831. The higher the score, the more positive the model predicts, the more positive. $Precision = \frac{TP}{TP+FP}$. Recall reached 0.98. The higher the Recall, the less the number of missed positive points. Recall $= 1$, i.e. all points labeled as Positive are recognized by the model. $Recall = \frac{TP}{TP+FN}$ However, to evaluate model quality, it is not possible to rely solely on Precision or Recall, instead one uses the F1 index as the harmonic mean. This index is calculated by the formula $\frac{2}{F1} = \frac{1}{precision} + \frac{1}{recall}$.



(a) Precision curve



(b) Recall



(c) F1-score

Fig. 4. Precision-Recall-F1

5 Conclusions

At the present time, the agriculture sector is still one of the important days, recognizing and being able to detect diseases in crops early can bring promotion to the agricultural industry.

In this case, we propose a leaf disease detection automatic using the Deep Learning technique using the Yolo-v5 algorithm [13] and the proposed stable feature. Up to the present time, when we compared to the 5740 tested images we have achieved 81,28% with detection rate and 91,93% with classification rate. Early detection of leaf diseases will be beneficial for the farmer helping the farmer to know the situation and solve the problems on the plants. However, the current method still has a limitation about the processing time of the encoding stage by using the auto-encoder. It is necessary to increase the performance of this prepossessing state by implementing GPU in the future. Our future plan is to increase the detection rate as well as the classification rate to a higher level to be able to improve and accelerate the detection of leaf diseases. In addition, we also plan to integrate our system into E-commerce to make our solution to farmers in near future.

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Reinforcement Learning for Developing an Intelligent Warehouse Environment

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Abstract. Nowadays, warehouse optimization is one of the core components of logistics. With the development of artificial intelligence (AI) technology and the advancement of automation technology, building a smart warehouse is an important task. This paper presents the machine learning techniques and technologies for developing an intelligent warehouse. A reinforcement learning method is proposed to train a basic warehouse environment for an efficient storage policy. The experimental results help comprehend the building of the model of a neural network of the reinforcement learning algorithm and the characteristics of this technique. This study further helps to understand the basic concepts of machine learning techniques to develop an algorithm for smart warehouses.

Keywords: Smart warehouse · Reinforcement learning · Machine learning technique · Intelligent management systems · AI applications

1 Introduction

Recently, the fourth industrial revolution with the cornerstone of a combination of robots, artificial intelligence (AI), fast networking equipment, and big data has created many achievements in research for production and human life [1, 17, 24, 26]. Research and development of intelligence applications to reduce workforce and production optimization is an important task. Nowadays, human resource costs are constantly increasing, and businesses face tremendous pressure from fierce market competition [11]. Therefore, building a smart warehouse and intelligent management systems is becoming necessary

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to optimize production and storage. Warehouses are typically used to keep business goods in storage. Large corporations can either construct their own warehouses or rent warehousing services from warehousing service providers. Warehouse service management determines e-commerce firms' success or failure in the global market. The warehouse is an essential component of the logistics business since its operational efficiency has a significant impact on the overall performance of the logistics industry. Inbound management, inventory management, and distribution management are the three major activities of a warehouse [10].

Warehouses play a critical role in the supply chain of food and agricultural goods, especially in the Vietnamese market. The warehouse is an essential component of Vietnamese logistics, including transportation, forwarding, warehousing, and other value-added services [3]. It is critical to increase the logistical competitiveness [9]. Investment in information technology (IT) is critical to improve Vietnam's logistics and warehousing competitiveness [7]. IT will add momentum to the transition from traditional warehouses to smart warehouses to optimize warehouse performance while reducing logistics and operating energy costs. Barcode, RFID, AR, AGV, IoT, WMS, and warehouse communication are technologies that can be combined with AI technology to make the warehouses smarter. AI might help warehouse operations change by automating activities, integrating information, and analyzing data in order to improve warehouse efficiency. As a result, AI applications in warehouses were promoted in order to enhance warehouse process improvement and in turn, improve Vietnam's logistics industry's competitive advantage. However, AI is a very complex field. Accordingly, each specific requirement needs to be addressed by particular needs. According to recent surveys, up to 85% of AI efforts fail to meet their expectations [25]. The testbed facility will be outfitted with cutting-edge machines and technologies that can mimic various AI investing situations, thus providing investors with the confidence and data they may need to make critical choices. Manufacturing companies may use testbeds to test new technologies in a live production setting before implementing them in the real world [21]. Testbeds also demonstrate their value in the academic world. In [8, 15, 19], the notion of testbed has aided the acquisition of practical and theoretical knowledge. In most universities, students are expected to deal with a significant amount of theory. On the other hand, testbeds provide options for students to collaborate and solve challenges while developing and building the testbed [15].

An attempt is made to build a smart warehouse at the Eastern International University (EIU) in Vietnam as simulated in Fig. 1. The EIU smart warehouse is a constantly developing environment where research and teaching may be smoothly linked, allowing bachelor and master students to gain hands-on experience while offering a realistic testbed for scientists. The main goal of testbeds is to bring together the goals of many stakeholders to examine how an innovative technology works in practice and how it may help businesses gain a competitive advantage. Therefore, the EIU Smart Warehouse provides various possibilities for businesses to test innovative solutions while also learning more about the academic environment. Both students and professors can get experience working on real-world projects. Consequently, it has the potential to facilitate more efficient technology transfer between the universities and industries.

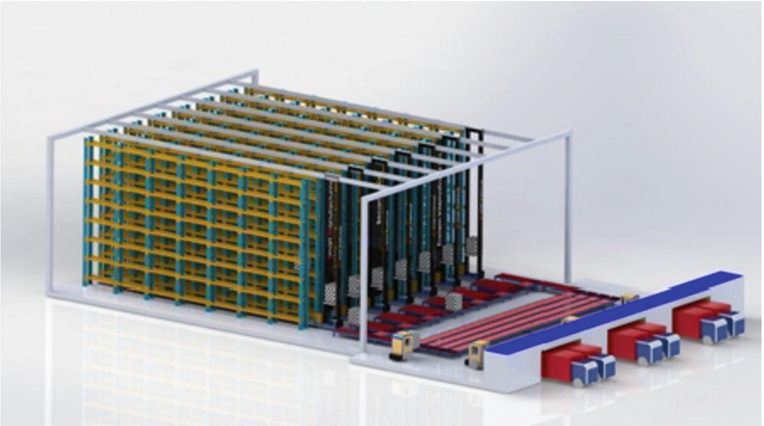

Fig. 1. Overview of the EIU smart warehouse with simulation.

This important project will assist enhance the quality of education in three EIU academic schools: Becamex Business School (BBS), School of Engineering (SOE), and School of Computing and Information Technology (CIT) in terms of effective teaching and learning. The project allows students from three schools to put theory into practice and make real-world selections. Students and researchers from BBS, SOE, and CIT can use the system to study a variety of topics including Motion control, PLC system, Industrial communication networks, Optimizing the sorting process, Intelligent systems, Warehouse Inventory management, Warehouse performance measurement, Applied computer vision, AI for the sorting process, Energy optimization, and Transaction time optimization. In terms of university business collaboration, this project acts as a testbed for firms to try out new technologies or solutions before putting them into practice. This is considered as an approach to promote the manufacturing process with significant cost savings and avoiding risks. Moreover, by maximizing the potential and value of local study, the EIU testbed benefits the local economy by attracting more investment and improving public service efficiency.

The EIU Smart Warehouse project is an application testing facility that uses a 1:10 miniature model (prototype) of a physical model with real-world features. The following are a list of hardware and software solutions:

- Hardware solution for smart warehouse.
  - Storage racks: 7 units can store up to 1372 pallets,
  - Automatic guided vehicle (AGV): 7 units,
  - Circulation conveyor system,
  - Sensor system (RFID) and technology solutions in smart warehouse management,
  - Controller (PLC) and control algorithm.
- Software solutions for smart warehouse.
  - Solutions to connect the physical controller system and management software,

– Solutions to optimize operating efficiency.

To develop an algorithm for a smart warehouse, an overview of machine learning techniques is presented with basic knowledge about four types of techniques: unsupervised learning, supervised learning, reinforcement learning, and imitation learning. This paper proposes the use of a reinforcement learning algorithm to perform an efficient storage policy and an optimization technique in a warehouse environment. An attempt is made to build a virtual warehouse environment and a robot with reinforcement learning for the optimization techniques. This experiment simulates and tests the robot using specified policies for reward and penalty with actions in a basic warehouse environment.

2 Machine Learning Techniques

Machine learning is a core part of artificial intelligence with many significant applications. Machine learning is diverse and complex, but in general, they are divided into four standard types, as shown in Fig. 2.

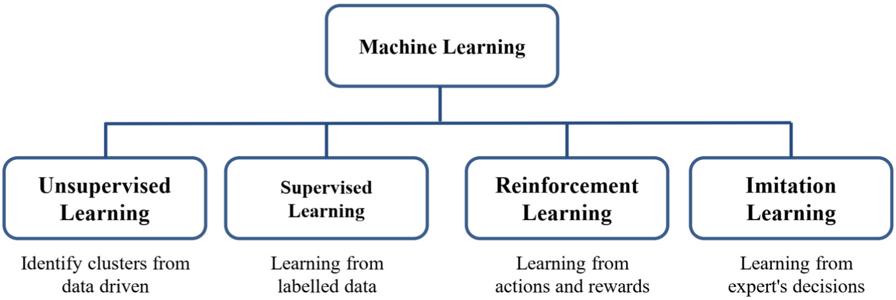

Fig. 2. Overview of machine learning technique using four types.

Unsupervised Learning is an algorithm that allows machines to learn on their own data to find similarities of features to identify the clusters or groups. This means that one only has the input dataset and do not label data. Unsupervised Learning is usually applied in clustering data as customer segmentation, targeted marketing, and recommended systems or dimensionality reduction of structure discovery, feature elicitation, meaningful compression, and big data visualization [5].

Supervised Learning is recently the most popular machine learning algorithms, especially computer vision and deep learning. This algorithm predicts new data output based on previously known training between the input data and labeled data (outcome). Supervised learning is usually used for image classification (object detection, semantic segmentation, instance segmentation), regression for weather forecasting, market forecasting, stock predictions, and estimating the object pose [24].

Reinforcement Learning is a machine learning technique that enables a machine to learn in a sequence of decisions, self-trained on reward and penalty for the actions it performs [4]. Machines learn in an interactive environment receiving some feedback from their actions and experiences. In reinforcement learning, the target is to explore a suitable action model to maximize the total cumulative reward. The reinforcement learning algorithm is popular in real-time training robot navigation, learning tasks, game AI, skill acquisition, inventory management in supply chains [23], and real-time decisions of the robot [13, 18, 22].

Imitation Learning is closely related to reinforcement learning techniques for learning from demonstrations of expert behavior [6]. Imitation learning techniques learn with decision policies from an expert while reinforcement learning is a policy that maximizes long-term reward with experiments from actions. Imitation learning has benefited from recent advancements in core machine learning techniques and the advancements of deep learning. This method depends on expert knowledge and the accuracy is also a subsidiary of expert demonstrations along with the expert policies. Imitation learning technique is usually applied in autonomous vehicles, autonomous driving systems [1], autonomous navigation [17], and training real-time robot manipulation [14].

3 Results and Discussion

The use of a reinforcement learning algorithm to train an efficient storage policy in a warehouse environment is proposed and described in this section. The task of reinforcement learning algorithm is to provide a diversity of methods to solve decision problems [20]. Reinforcement learning is proposed to solve inventory management problems [23] and supply chain optimization [2]. In [16], Kamoshida et al. proposed an automated guided vehicle route planning policy in a warehouse environment using deep reinforcement learning. They improved the efficiency of the picking activities limited by the five order data and one warehouse flatform.

This section establishes a simple warehouse environment to develop reinforcement learning to train a robot as simulated in Fig. 3. Reinforcement learning is an algorithm that builds robots self-trained on reward and punishment mechanisms.

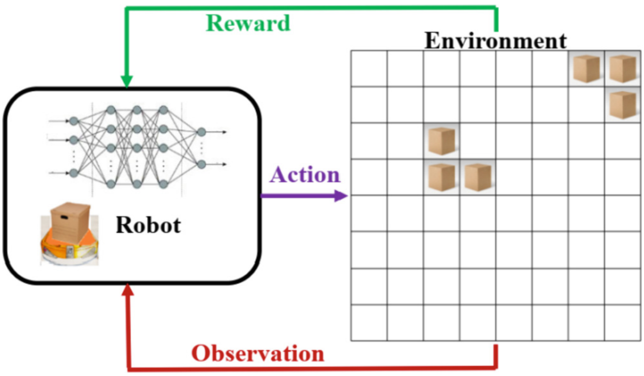

Fig. 3. Overview of the basic of reinforcement learning where the robot is learning in a simple warehouse environment.