Automated Machine Vision Inspection System for Applying Plastic Lids on Wet Wipes Packs

Jafar Abukhait
Department of Computer and Communications Engineering., Faculty of Engineering, Tafila Technical University, Tafila, Jordan
Email: jafar@ttu.edu.jo (J.A.)

***Abstract*—Computer vision techniques have been widely used in industrial manufacturing for automation, monitoring, quality assessment and inspection. Specifically, some techniques are being deployed to detect and identify products' defects instead of human operators. In this paper, a vision system is proposed to inspect and assess the quality of applying plastic lids on wet wipes packs at a manufacturing company in Jordan. Currently, the manufacturing company uses automatic lid applicator that has no visual control system and thus, a human operator is needed to inspect every pack. This process includes detecting the position and orientation of each lid to assure that it has been applied correctly at the center of the pack above specific label. Automating this inspection process would save time and efforts and increase the productivity. The proposed inspection system has the following modules: (1) Pack and lid detection and segmentation using YOLOv8s-Seg algorithm; (2) distance to border (DtB) extraction between the pack centroid and lid boundary; and (3) inspection module using linear Support Vector Machine (SVM). A segmentation dataset of 319 different images of wet wipes packs was constructed using the Segment Anything Model (SAM). The proposed inspection has been tested on different wet wipes packs. Experimental results successfully demonstrated the efficiency of the inspection system.**

***Index Terms*—Inspection system, wet wipes segmentation, YOLOv8-Seg, support vector machine, segment anything model, machine vision**

I. Introduction

In today's fast-paced manufacturing industry, machine vision is paramount. The applications of vision in industries may be classified broadly into: gauging, identification, guidance and inspection [1]. Inspection is a crucial step of any manufacturing process which aims to rejecting nonconforming products and assuring good quality parts [2]. Over the past three decades, machine vision systems have effectively supplanted the labor-intensive traditional visual inspection methods in various industries.

One area where machine vision systems are of utmost importance is in the packaging of consumer goods [3]. Ensuring that products on assembly lines are being packaged accurately and securely is not only essential for product integrity but also for customer satisfaction. To assure the quality of products, in terms of packaging, manufacturers typically assign human operators to monitor and inspect products on the assembly line. This manual inspection process demands a great effort and high speed response by the human operator over the assembly line. In addition, human distraction and deficiency could lead to inspection failures [3, 4]. Failure to detect packaging defects early in the process costs time, money, and consumer satisfaction. To meet these demands, modern manufacturing facilities are increasingly turning to automated vision-based inspection systems. This cutting-edge technology combines the power of automation and advanced image processing to guarantee precise packaging while simultaneously verifying product quality. Automated packaging inspections can be deployed efficiently on any type of products over any assembly line.

Currently, a wet wipes manufacturing company in Jordan uses automatic lid applicator to apply plastic lids on wet wipes packs. The plastic lid should be applied accurately over a sticky label which in terms preserves the wet wipes papers inside the packet. Failure to apply the plastic lid accurately degrades the packaging quality, lowers consumer satisfaction and complicates appropriate consumer usage. The manufacturing company depends on human operator to inspect the packaging process and assure its quality. This traditional manual inspection process, while effective to a certain extent, is limited by human error, fatigue, and speed constraints. This is where automated vision-based inspection systems step in, revolutionizing the inspection process by providing consistent, high-speed, and accurate assessments of lid placement.

This work presents a machine vision inspection system of wet wipes lid application process. The proposed system achieves the inspection task by cascading several modules. Firstly, it deploys YOLOv8 detector in segmenting both wet wipes lids and packs. Secondly, distance to border (DtB) descriptor is suggested and deployed to measure the lid alignment with respect to the pack for each wet wipes. Finally, classification of wet wipes lid application is fulfilled based on linear support vector machine (SVM). The effectiveness of the proposed system is validated on different wet wipes categories. The major offerings of this research paper are summarized as follow:

- Constructing a novel two-label segmentation dataset for both wet wipes lids and packs.

Manuscript received December 18, 2023; revised January 27, 2024; accepted February 2, 2024.

- Implementation a segmentation model using YOLOv8s-seg algorithm and evaluating its performance effectiveness on the dataset.
- Categorization the wet wipes lid application process to correct, wrong positioning or wrong orientation based on linear SVM.
- Deploying DtB descriptors innovatively to describe the geometric alignment between the wet wipes lids and packs.

The performance of proposed scheme is evaluated for 2-class and 3-class, and 10-class lid application process based on accuracy, precision and recall.

The rest of the article is prepared as follows: Section II provides a background of machine vision systems on inspection, especially on packaging inspection, and approves its significance. Section III demonstrates the inspection system cascaded modules and gives brief information regarding material and methods required for the implementation of the proposed system. Section IV evaluates the system performance experimentally based on certain metrics. Lastly, Section V elaborates the conclusions.

II. Significance and Background

In this era of Industry 4.0, where automation and data-driven decision-making are central to manufacturing success, the adoption of automated vision-based inspection systems is not just a convenience; it is a necessity. These systems leverage sophisticated cameras, machine learning algorithms, and real-time data analysis to identify and rectify issues in real-time, reducing costly rejections, waste, and the need for manual labor [5]. In general, vision-based inspection systems are deployed in many economic sectors such as: industry [6], agriculture [7] and transportation [8, 9]. It can be categorized to classical-based and deep learning-based techniques [10].

The application of Automated Vision-Based Inspection Systems in the context of product packaging or defect detection has emerged as a pivotal area of research and development within the manufacturing industry [3, 11]. A review of the literature reveals the significance of this technology in enhancing both the efficiency and quality of the production process. Various studies have highlighted the system's capability to provide real-time monitoring and precise control over product packaging, which significantly reduces the subsequent product defects [12–15].

This work presents a machine vision inspection system of wet wipes lid application process. The plastic lid should be applied accurately over a sticky label which in terms preserves the wet wipes papers inside the packet. Failure to apply the plastic lid accurately on the specified position with appropriate orientation degrades the packaging quality, lowers consumer satisfaction and complicates appropriate consumer usage.

The proposed system leverages high-resolution imaging and machine learning techniques to analyze lid placement on wet wipes packs over an assembly line. It enables precise detection of faulty lid application process. This system swiftly identifies lid application flaws with remarkable accuracy, ensuring consistent quality standards and minimizing human error. The benefits of this system are manifold: increased efficiency in the inspection task, enhanced product quality assurance, reduced operational costs through early error detection. Additionally, this system offers real-time monitoring, adaptability to varying conditions and various categories of wet wipes.

III. Proposed Inspection System

The proposed inspection system, as shown in Fig. 1, follows three cascaded modules:

1. Pack and lid segmentation: a model-based segmentation based on YOLOv8-seg convolutional neural network (CNN) is implemented to detect both the wet wipes pack and lid and segment their boundaries for each image.
2. Distance to border extraction: a feature vector of the Euclidean distance between the centroid of the wet wipes pack and the lid boundary is constructed.
3. Inspection module: this module detects any defect of lid applying and decides if applying process on the pack is acceptable in terms of orientation and position. This is achieved by implementing a classification model using linear support vector machine (SVM).

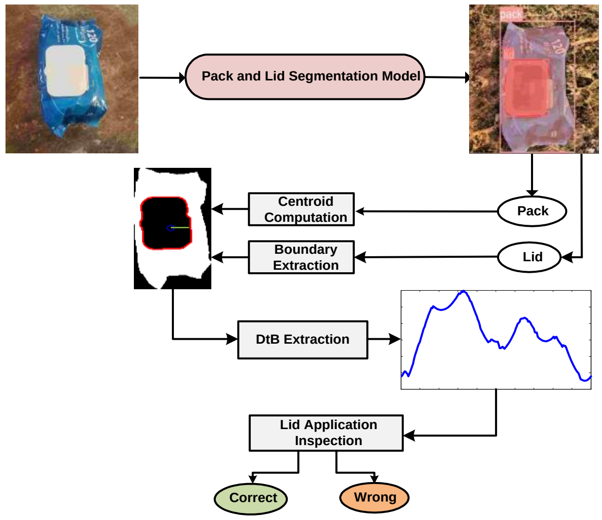

Fig. 1. The proposed inspection system.

A. Pack and Lid Segmentation

In this module, a segmentation model is implemented using YOLOv8-seg convolutional neural network. The goal of this model is to segment both the wet wipes packs and lids and retrieve their boundaries. These boundaries would be used on the next modules of the inspection system to assess the alignment of the lid with respect to the wet wipes pack.

A segmentation dataset has been constructed using hundreds of different wet wipes images. Then, the segmentation model has been trained, validated and tested to evaluate its performance using various metrics.

1) Segmentation dataset construction

Initially, a set of 319 images were acquired for five different categories of wet wipes. These categories differ in colors and sizes as shown in Fig. 2. This original dataset has wet wipes of both correct and wrong lid application.

Fig. 2. Samples of the five different categories of wet wipes.

(a)

(b)

Fig. 3. Annotation process on Roboflow platform for wet wipes: a) lids; b) packs.

Several steps were followed to prepare the dataset:

- All images were captured manually under different illumination conditions to assure the robustness of the segmentation during daytime and nighttime. The resolution of images is 816×1088×3.
- All images were uploaded to Roboflow platform and annotated using the Smart Polygon tool. The annotation process involves drawing a boundary contour around both the wet wipes pack and lid and assigning separate labels for these two classes. Thus, we have used the Segment Anything Model (SAM) which is deployed as an API in the smart polygon annotation tool on Roboflow [16]. This tool allows users to either draw a bounding box around the object or click on any part of the object. In both cases, the SAM model will predict the boundary of the object. User can correct the boundary in case it was not drawn accurately. Fig. 3 shows the annotation process steps' sequence.
- Images were preprocessed by firstly resizing them to 640×640. Then, adaptive equalization has been applied to these images to adjust their contrast.
- Augmentation operations were done randomly to simulate various imaging conditions. Brightness, between –25% and 25%, has been achieved on part of the images. Other variability brightness values were added to some images to simulate lighting and camera setting changes. In addition, Gaussian blur has been deployed on another portion of the images to simulate camera focus changes.
- After augmentation, the dataset has been generated to include 765 images divided as: 669 for training, 64 for validation and 32 images for testing.

2) Model training and evaluation

The segmentation model has been implemented using Convolutional Neural Network (CNN) in which deep features of objects are learned through the network layers. YOLOv8s-Seg segmentation architecture has been specifically selected to train and validate a multi-label segmentation model to detect and segment both the wet wipes packs and lids. The choice of YOLOv8 was based on its computational and accuracy efficiency. The main difference between YOLOv8-det (detection) and YOLOv8-Seg (segmentation) is primarily in their final layers and how they process the output [17]. The detection model typically concludes with layers that predict bounding boxes, object classes, and confidence scores. On the other hand, for segmentation, the model is structured to output pixel-wise class predictions, enabling us to not only identify objects but also delineate their precise boundaries within an image. For detailed descriptions of YOLOv8 architecture, refer to [18].

Several performance metrics and loss functions were adopted to measure the segmentation model during training and validation which are: mean average precision (mAP), intersection over union (IoU), precision, recall, box loss, class loss and segmentation loss. These metrics are explained and demonstrated, in this work, as follows:

- Precision (P): it measures the number of relevant segmentation regions (maps) to the total number of segmented regions according to the formula in (1):

$$Precision = \frac{TP}{TP+TN}. \tag{1}$$

- Recall (R): it measures the number of relevant segmented regions (maps) retrieved to the number of relevant segmented regions in the annotated dataset according to the formula in (2):

$$Recall = \frac{TP}{TP+FN}. \tag{2}$$

where TP is the number of correctly predicted segments (lid or pack) over an overlapping threshold with respect to the ground truth, FP is the number of mispredicted segments, FN is the number of segments that the model failed to predict.

- *Intersection over union (IoU)*: it measures the amount of predicted segmented region (map) that overlaps with the ground truth segmented region divided by the total area of both segmented regions [19].

- *Mean average precision (mAP)*: it measures the accuracy by considering both the precision and recall at different levels of confidence thresholds [20].
- *mAP@0.5*: it measures the accuracy of object segmentation at IoU > 0.5 overlap between predicted and ground-truth masks.
- *Bounding box loss*: it calculates the error between the predicted and the ground truth boxes' geometry. It measures how well the model predicts the size and location of the bounding boxes [21].
- *Objectness loss*: it determines how confident the model is about the presence of an object in the bounding box. It contrasts the model's probability of an object being present with the ground truth value.
- *Segmentation loss*: it quantifies how close the predicted segmentation map is to the ground truth map. It measures how effectively the model performs the semantic segmentation task [22].

B. Distance to Border Extraction

In this module, a feature vector of the distances between the centroid of the wet wipes pack and the lid boundary is constructed. This vector is named as DtB vector and it is usually used to obtain the geometric shape of object. In this module, DtB has been deployed to measure the geometric alignment of wet wipes lids with respect to wet wipes packs. This shape feature extractor has been achieved by computing the Euclidean distances between the centroid of segmented wet wipes pack and the segmented lid boundary. Wrong applying of wet wipes lids (with regard to orientation or position) would lead to different DtB vector when comparing with appropriate applying process as shown in Fig. 4. This difference in DtBs happens because the centroid of each wet wipes pack would be geometrically aligned on different positions on the wet wipes lid surface.

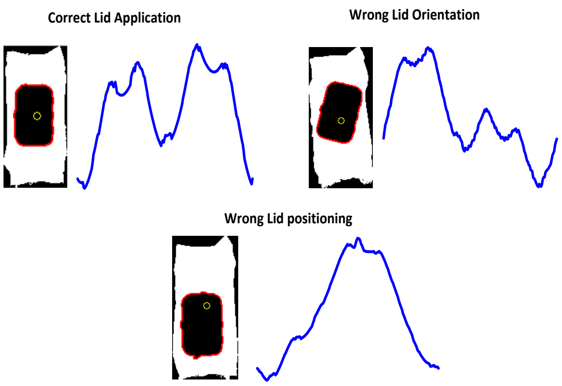

Fig. 4. DtB descriptors of correct and wrong lid application.

The DtB shape feature vector is computed based on the following steps:

- The centroid of the wet wipes pack is defined over the filled area of its segmented region as the mean of all *x*-axis points and the mean of all *y*-axis points:

$$x_c = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

$$y_c = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

where x_i and y_i are the ith pixel coordinates in the filled area within the underlying region.

- DtB is defined as the Euclidean distance from the centroid (x_c, y_c,) to the boundary pixels of the wet wipes lid from θ = 0 °to 360 °as:

$$\text{DtB} = \sum_{\theta=0}^{360} \sqrt{\left[x_c - x_b(\theta)\right]^2 + \left[y_c - y_b(\theta)\right]^2} \tag{5}$$

- DtB has been normalized with respect to the maximum value to make it invariant to scale.
- DtB is also resized to fix size to make it invariant with respect to objects' sizes.

C. Inspection Module

This module evaluates the wet wipes lid application process and decides if lid alignment on the pack is correct in terms of orientation and position. Two classification models have been implemented for inspection: 1) binary classification model which aims to evaluate the lid application process either to correct or wrong; 2) ternary classification model which aims to evaluate lid application process to correct, wrong orientation, or wrong positioning. Linear Support Vector Machine (SVM) is used in both classification models. The input to linear SVM is the DtB vectors generated in the previous module. The dataset was partitioned to two classes (wrong and correct) for the binary classification model while it was partitioned to three classes (correct, wrong orientation, and wrong positioning) for the ternary classification model. The dataset, in both models, was labeled by a human expert who is currently responsible for the current manual inspection process on the production line at the wet wipes factory. It is worth to mention that the ternary classification model was implemented using the SVM classifier in a one-versus-all fashion (as shown in Fig. 5) which requires constructing two cascaded classification models.

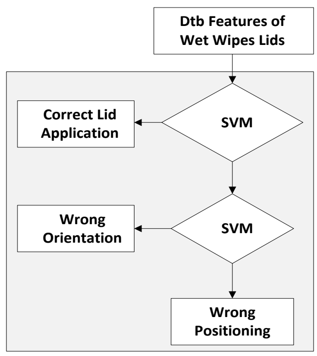

Fig. 5. The ternary classification model for inspecting the wet wipes lid application.

The concept of SVM stands on suggesting the optimal hyperplane that maximize the margin between the hyperplane itself and the closest vectors belonging to both classes [23–25]. The choice of using linear SVM is more suitable than nonlinear SVM because of the nature of the training data, being a 1-dimensional vector and the data of each class is separable. Each classifier has two phases: training and testing.

The training data are labeled as:

$$\{\vec{x}_i, y_i\} \text{ where } i = 1,\ 2,\ \cdots,\ n;\ \vec{x}_i \in \Re^d; y_i \in (-1,\ 1);$$

$\vec{x}_i$ is the DtB vector, y_i is the class which can attain the values of –1 or 1, i is the number of training data, and d is the dimension of the DtB vector.

The hyperplane separating the two classes can be represented by:

$$\vec{w}\vec{x} + b = 0 \tag{6}$$

where $\vec{w}$ (weight) is the orthogonal vector to the hyperplane determining it's orientation, and b (bias) is the distance from the origin to the hyperplane.

Several performance metrics were adopted to measure the classification performance as follows:

- Precision: it represents the ratio of relevant classifications (TP) to the total number of elements and it follows the same formula of (1).
- Recall: it represents the ratio of relevant classifications (TP) to the number of classes in the database and it follows the same formula of (2).
- Classification accuracy: it measures the correct classifications to all class instances in the dataset and it can be calculated according to:

$$\text{Accuracy} = \frac{T_p + T_n}{\text{All Classifications}} \tag{7}$$

where TP and TN are the instances (correct application, wrong application) correctly classified by the model and they are on the main diagonal of the confusion matrix.

IV. Experimental Results

In this section, we demonstrate the performance of both the segmentation and inspection models. Segmentation model is based on YOLOv8 architecture and aims to automatically segment the wet wipes packs and lids and retrieve their boundaries. Additionally, we demonstrate and discuss the effectiveness of the two inspection models which are based on SVM classifier.

A. Segmentation Model Results

The segmentation model was implemented using YOLOv8s-seg architecture from Ultralytics YOLOv8.0.28 framework. It was trained on a Tesla T4 GPU. The hyperparameter settings: learning rate, batch size, weight decay, epochs and image size were selected as shown in Table I.

TABLE I: Hyperparameters during Training

Hyperparameter	Value
Learning Rate	0.01
Weight Decay	0.0005
Batch Size	64
Image Size	640×640 pixels
Epochs	129

The training process was initialized to 200 epochs but it was stopped after 129 epochs since no improvement has been achieved in the last 50 epochs.

Experimental results of wet wipes lid and pack segmentation model training is shown in Fig. 6. These results are based on augmented dataset which was trained using hyperparameters optimization and transfer learning. It is noticed that box loss, segmentation loss and class loss are converging with 0.1998, 0.185 and 0.1717, respectively.

The model utilizes both Recall and mAP@0.5 to evaluate its efficiency in object segmentation and its proficiency in correctly classifying objects. It achieved 98.5% and 99.2% for both recall and mAP@0.5.

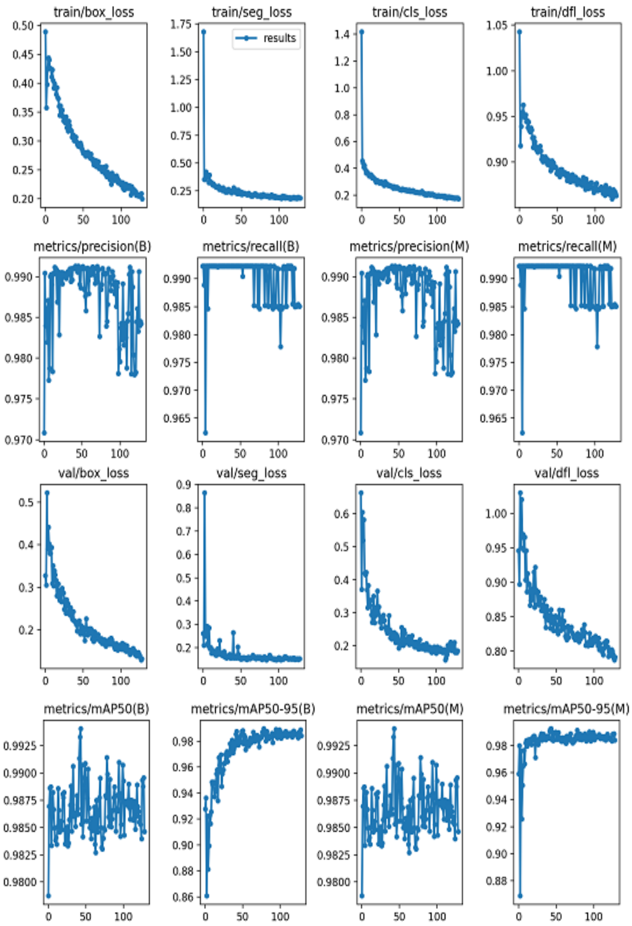

Fig. 6. Performance metrics throughout the training process including: class loss, box loss, segmentation loss, recall, precision and mAP@0.5.

The confusion matrix, as shown in Fig. 7, provides a detailed breakdown of the model's performance, including true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) for each object class (e.g., lid, pack and background).

To perform model testing, we loaded the saved weights of the trained model and passed the test dataset through it. Fig. 8 shows some examples of segmentation model Inference. Over the 32 test images, where one lid and one pack are existed in each one, the segmentation model succeeded to segment each lid and pack. For one test image, the model had two segments of the pack. Regarding the inference time, given that all images have a 640×640 resolution, the model had registered an average inference time of 18.7 ms. The lowest inference time was

18.2 ms and the highest was 20.6 ms. This inference time was achieved on Tesla T4 GPU.

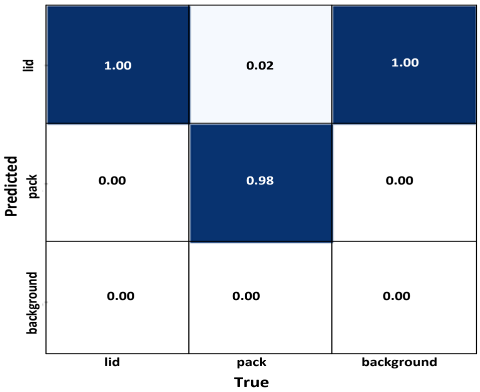

Fig. 7. Confusion matrix of the segmentation model.

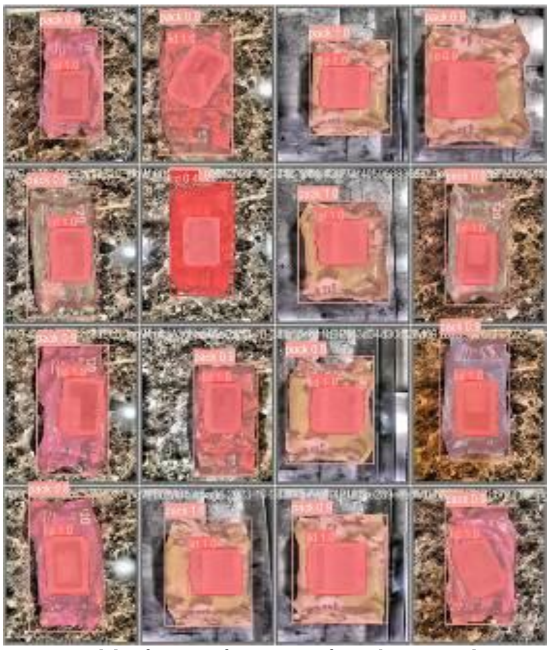

Fig. 8. Model Inference of 16 images from the testing dataset.

B. *Inspection Models' Results*

In this module, we demonstrate the results of the inspection models including the DtB feature descriptors, the dataset division between training and testing sets. Two inspection models have been implemented: binary classification (categorize the lid application process to either correct or wrong) and ternary classification (categorizes the lid application process to correct, wrong positioning or wrong orientation).

A dataset of 298 wet wipes images has been used in both the training and testing phases of the binary classification model while 228 different images were used in the ternary classification model. In both models, we have prepared the data to be balanced among the different classes. Table II shows the exact division of dataset images in both classification models. The dataset images have been categorized by a human expert who works currently as a manual inspector on the manufacturing line of wet wipes factory in Jordan.

DtB has been deployed to measure the geometric alignment of wet wipes lids with respect to wet wipes packs.

TABLE II: WET WIPES IMAGES DATASET DIVISION

Check item	**Classification model**	
Lid application status	Binary	Ternary
Correct	150	80
Wrong orientation	148	72
Wrong positioning		76
Total	298	228

A feature descriptor of each image in the dataset is extracted based on DtB shape extraction algorithm. This shape feature extractor has been achieved to compute the Euclidean distances between the centroid of segmented wet wipes pack and the segmented lid boundary. The DtB vector has been sampled to specific size which is 200 and normalized with respect to the maximum value to make it invariant to scale. It is worth to mention that all DtB distances were measured from $\theta=0°$ to $\theta=360°$ counter clock wise.

Fig. 9, Fig. 10 and Fig. 11 show examples of wet wipes images containing correct lid application and wrong lid application along with the DtB vectors being displayed to demonstrate visually the differences.

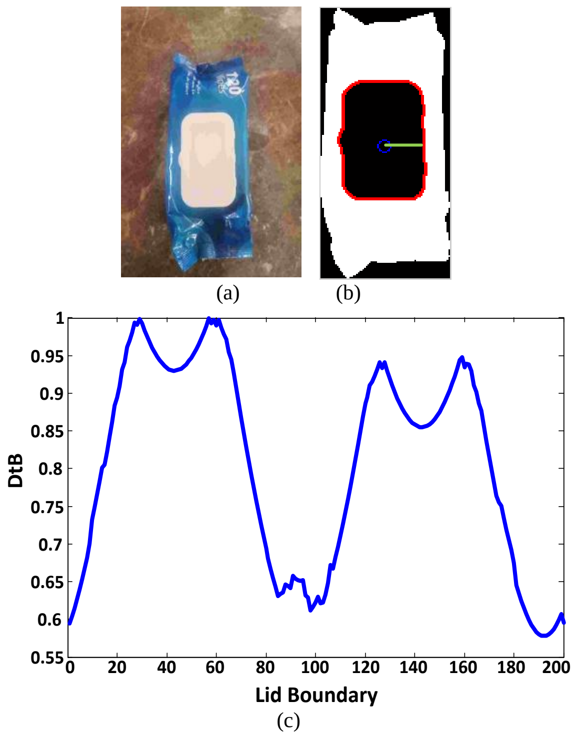

Fig. 9. Example of DtB feature description results of correct wet wipes lid application showing: a) original images; b) segmented image along with lid boundary; c) proposed DtB feature descriptor.

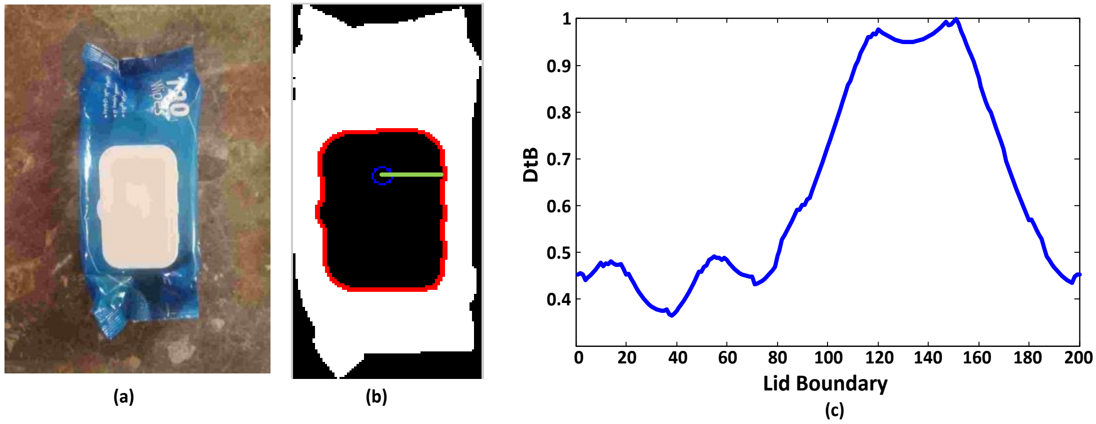

Fig.10. Example of DtB feature description results of wrong positioning wet wipes lid application showing: (a) original images; (b) segmented image along with lid boundary; (c) proposed DtB feature descriptor.

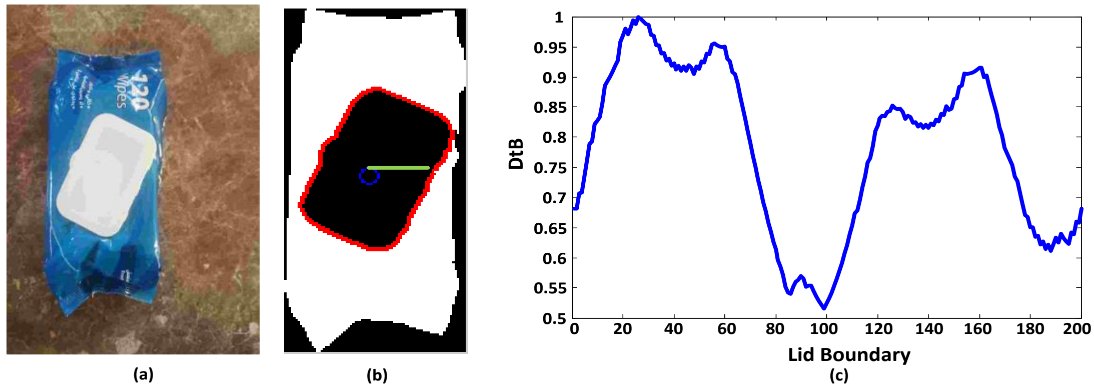

Fig.11. Example of DtB feature description results of wrong orientation wet wipes lid application showing: (a) original images; (b) segmented image along with lid boundary; (c) proposed DtB feature descriptor.

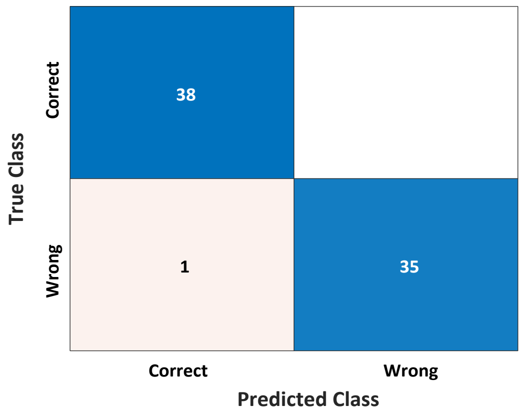

Fig. 12. Confusion matrix of the binary classification model for the inspection process.

1) Binary classification results

DtB vectors were deployed as inputs to implement a binary classifier model using linear support vector machine. This model aims to classify the wet wipes lid application process either to correct or wrong. 298 different and labeled images were used to train and test the model. These images were partitioned to 75% (224 images) for training and 25% (74 images) for testing. Fig. 12 shows the confusion matrix of the classification results for the 74 test images. Precision, Recall and accuracy are: 97.4%, 100%, and 98.6%, respectively.

2) Ternary classification results

Additionally, a ternary classification model was implemented to classify the wet wipes lid application process to correct, wrong orientation or wrong positioning. DtB vectors were deployed as inputs to implement this model using linear support vector machine in a one-versus-all fashion. The dataset has been constructed to be balanced by selecting approximately an equal number of images for each of the three classes. 228 different and labeled images were used to train and test the model. These images were partitioned to 75% (170 images) for training and 25% (58 images) for testing. Fig. 13 shows the confusion matrix of the classification results for the 58 test images. Precision, Recall and accuracy are: 96.9%, 96.5%, 96.6%, respectively.

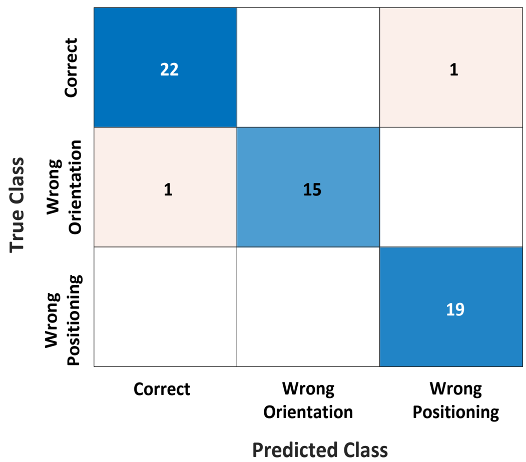

Fig. 13. Confusion matrix of the ternary classification model for the inspection process.

V. Conclusions

In this work, a machine vision system was proposed to inspect and assess the quality of applying plastic lids on wet wipes packs at a manufacturing company in Jordan. The manufacturing company uses automatic lid applicator that has no visual control system and thus, a human operator is needed to inspect every pack. We have implemented the automated inspection system as a set of cascaded modules through which latest emerging computer vision techniques have been deployed. We have started our inspection model by constructing a segmentation dataset for the wet wipes lids and packs. The segmentation dataset had included 319 different images of wet wipes packs and was constructed using the Segment Anything Model (SAM). We also implemented a segmentation model using YOLOv8s-Seg algorithm. The inspection module deployed distance to border (DtB) descriptor between the pack centroid and lid boundary as an input features to linear support vector machine (SVM). The proposed inspection has been tested on different categories of wet wipes packs and experimental results successfully demonstrated the efficiency of the inspection system where the segmentation model achieved a mAP@0.5 value of 99.2%, and the accuracy of the inspection module was 98.6% and 96.6% for the binary and ternary classification models, respectively.

Conflict of Interest

The author declares no conflict of interest.

References

[1] R. Senthilnathan, "Deep learning in vision-based automated inspection: current state and future prospects," in *Machine Learning in Industry*, S. Datta and J. P. Davim Ed. 2022, pp. 159–175.

[2] M. Park, and J. Jeong, "Design and implementation of machine vision-based quality inspection system in mask manufacturing process," *Sustainability*, vol. 14, no. 10, #6009, 2022.

[3] V. Chauhan, and B. Surgenor, "A comparative study of machine vision based methods for fault detection in an automated assembly machine," *Procedia Manufacturing*, vol. 1, pp.416–428, 2015.

[4] Z. Ren, F. Fang, N. Yan, and Y. Wu, "State of the art in defect detection based on machine vision," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 9, no. 2, pp. 661–691, 2022.

[5] A. Charan, C. K. Chowdary, and P. Komal, "The future of machine vision in industries-a systematic review,"*IOP Conference Series: Materials Science and Engineering*, vol. 1224, no. 1, #012027, 2022.

[6] J. Abukhait, "An automated surface defect inspection system using local binary patterns and co-occurrence matrix textures based on SVM classifier," *Jordan Journal of Electrical Engineering*, vol. 4, no. 2, pp. 100–113, 2018.

[7] A. Aljaafreh, E. Y. Elzagzoug, J. Abukhait, A. H. Soliman, S. S. Alja'Afreh, A. Sivanathan, and J. Hughes, "A real-time olive fruit detection for harvesting robot based on Yolo algorithms," *Acta Technologica Agriculturae*, vol. 26, no. 3, pp. 121–132, 2023.

[8] J. Abukhait, "Visibility estimation of road signs considering detectability factors for driver assistance systems," *WSEAS Trans. on Signal Processing*, vol. 12, pp. 111–117, 2016.

[9] J. Abukhait, I. Zyout, and A. M. Mansour, "Speed sign recognition using shape-based features," *International Journal of Computer Applications*, vol. 84, no. 15, pp. 32–37, 2013.

[10] M. Bahaghighat, F. Abedini, M. S'hoyan, and A. J. Molnar, "Vision inspection of bottle caps in drink factories using convolutional neural networks," in *Proc. of 2019 IEEE 15th Int. Conf. on Intelligent Computer Communication and Processing*, 2019, pp. 381–385.

[11] M. Kazmi, B. Hafeez, H. R. Khan, and S. A. Qazi, "Machine-vision-based plastic bottle inspection for quality assurance," *Engineering Proceedings*, vol. 20, no. 1, #9, 2022.

[12] M. Gao, D. Ren, Y. Hu, L. Fu, and L. Qiu, "Ampoule packaging quality inspection algorithm based on machine vision and lightweight neural network," *Journal of Computer Applications*, vol. 40, no. 10, #2899, 2020.

[13] M. A. Ali and A. K. Lun, "A cascading fuzzy logic with image processing algorithm–based defect detection for automatic visual inspection of industrial cylindrical object's surface," *The International Journal of Advanced Manufacturing Technology*, vol. 102, pp. 81–94, May 2019.

[14] O. Badmos, A. Kopp, T. Bernthaler, and G. Schneider, "Image-based defect detection in lithium-ion battery electrode using convolutional neural networks," *Journal of Intelligent Manufacturing*, vol. 31, pp. 885–897, Apr. 2020.

[15] J. Z. Diaz, M. A. Farooq, and P. Corcoran, "Automatic inspection of seal integrity in sterile barrier packaging: A deep learning approach," *IEEE Access*, 2024, doi: 10.1109/ACCESS.2023.3348779.

[16] A. Kirillov, E. Mintun, N. Ravi *et al*., "Segment anything," *arXiv preprint*, arXiv:2304.02643, 2023.

[17] X. Yue, K. Qi, X. Na, Y. Zhang, Y. Liu, and C. Liu, "Improved YOLOv8-Seg network for instance segmentation of healthy and diseased tomato plants in the growth stage," *Agriculture*, vol. 13, no. 8, #1643, 2023.

[18] Whats new in YOLO8. [Online]. Available: https://blog.roboflow.com/whats-new-in-yolov8/

[19] H. Rezatofighi, N. Tsoi, J. Gwak, A. Sadeghian, I. Reid, S. Savarese, "Generalized intersection over union: a metric and a loss for bounding box regression," in *Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition*, 2019, pp. 658–666.

[20] T. Nguyen, K. Vandevoorde, N. Wouters, E. Kayacan, J. G. De Baerdemaeker, W. Saeys, "Detection of red and bicoloured apples on tree with an RGB-D camera," *Biosystems Engineering*, vol. 146, pp. 33–44, 2016.

[21] A. Abbas, "Object detection on large-scale egocentric video dataset," Master dissertation, University of Stirling, Stirling, UK, 2018.

[22] S. Jadon, "A survey of loss functions for semantic segmentation," in *Proc. of 2020 IEEE Conf. on Computational Intelligence in Bioinformatics and Computational Biology*, 2020, pp. 1–7.

[23] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining and Knowledge Discovery*, vol. 2, no. 2, pp. 121–167, 1998.

[24] N. Cristianini, and J. Shawe-Taylor, *An Introduction to Support Vector Machines*, Cambridge: Cambridge University Press, 2000.

[25] V. N. Vapnik, *The Nature of Statistical Learning Theory*, New York: Springer-Verlag, 1995.

Jafar Abukhait received his B.Sc. and M.Sc. degrees in Computer Engineering from Yarmouk University in 2005 and 2007, respectively. He received his Ph.D. degree in Electrical and Computer Engineering from Western Michigan University in 2012. In 2012, he joined the Faculty of Engineering at Tafila Technical University as an Assistant Professor of Electrical and Computer Engineering. He got promoted to Associate Professor in 2018. His research interests are mainly in digital image processing, feature extraction, computer vision, and classification techniques.