Proposal of Augmentation Pipeline for Automated Pill Inspection Via YOLOv5

Arsalan Zahid
Huddersfield University
Huddersfield, HD1 3DH, United Kingdom

Abstract:- The inspection of pharmaceutical products, especially pills, has become an essential process in the pharmaceutical industry to ensure the quality and safety of medication. The traditional inspection methods are time-consuming and prone to errors. The use of deep learning models such as YOLOv5 has shown promising results in detecting and classifying pills accurately. YOLOv5 is a state-of-the-art object detection model that provides faster and more efficient processing of images with high accuracy rates. In this abstract, we review the recent studies on pill inspection using YOLOv5. We discuss the key features of YOLOv5 that make it suitable for pill inspection and the challenges associated with this task. We also highlight the potential benefits of using YOLOv5 for pill inspection, including improved accuracy, speed, and cost-effectiveness. Overall, the application of YOLOv5 in pill inspection can help ensure the authenticity and integrity of pharmaceutical products, providing a valuable tool for quality control in the pharmaceutical industry. The MAP @ 0.5 obtained was 1 after 25-27 epochs.

Keywords:- Defect Detection; Micro-cracks; Photovoltaics; Smart Manufacturing; Quality Inspection.

I. INTRODUCTION

Computer vision has started to penetrate many industries including healthcare [1,2], pallet racking [3], renewable energy [4,5,6] and defect detection [7,8] in general. Pill inspection is a very important process carried out in pharma industries. Detecting pill defects involves old traditional methods which have several disadvantages such as manual labor is used which is time consuming and costs a lot due to the workforce required. The use of manual labor involves error in detecting the defects. [9]

Adverse drug events (ADEs), which are harms brought on by medication action linked to a drug, can result from mistakes in the prescription or administration of a drug pill [10]. Correct pill identification can enhance patient care and poison control center operations. The U.S. Institute of Medicine claims that medication error is the most avoidable medical error in recent studies [11].

In this paper, we propose an automated pill inspection system using machine learning. We have implemented YOLO v5 on the original dataset and augmented dataset. Finally, after achieving the results, we have compared all the

mAP_0.5 precision and analyzed the performance. The results are evidence of how machine learning can benefit the pill manufacturers with less cost, less labor and error free results. Continuous loading and unloading, environmental conditions, and friction can gradually weaken the rack's structural integrity, leading to rust, corrosion, or deterioration. Additionally, external forces like earthquakes, extreme weather conditions, or impacts from heavy objects can threaten the integrity of pallet racking systems [1], compromising their structural integrity and posing significant risks to personnel and stored goods. Detecting and addressing damaged pallet racking in a timely manner is essential to prevent accidents, minimize product loss, and ensure the smooth operation of warehouse logistics.

II. LITERATURE REVIEW

The existing literature on pill inspection with Yolo V5 indicates a scarcity of proactive research in this area; there are only a few publications on pill inspection. As a result, we have expanded our literature review to inspect damaged pills.

Cheng [12] proposed a lightweight deep convolutional neural network machine learning model which contained a YOLO machine algorithm to detect faults in pharmaceuticals. The main objective of the research is quality inspection. To address the case of uniformly colored drug attachment in drug images, a color drug image segmentation algorithm combining the HSV model and color distance is adopted. The author claims that the accuracy results were 86 percent and outweighed the results obtained from traditional manual rechecking.

Mac [13] et al. proposed deep learning algorithms and computer vision-based processing that detects any crack or contamination. The writer highlighted that pill inspection requires more labor force, time consuming and gives non accurate results. The model uses features learned by Convolutional Neural Network and Adam optimization. The author claims that the model achieves an accuracy of 95 percent which is quite impressive.

Cai [14] et al. suggested a machine vision system for inspecting the quality of a dropping pill. The author highlighted that machine vision is not a destructive technology, is cost friendly and gives a higher accuracy. The inspecting quality contained non-spherical, abnormal sizes and colors to evaluate the quality of XDPs images quickly and accurately. The author gathered 270 mages with different

types of detects and the process was done. Three defective categories were created based on color and shape. The author claims that the Random Forest achieved a great accuracy of 98.52%, 100.00% and 100.00%. The author assures us that this has a lot of potential to identify defects in dropping pills.

Kim [15] et al. proposed a deep learning algorithm that can help in detecting pills with limited training data. The authors used an effective database for the multiplication of pills. The author has used data augmentation to give more accurate results. The author also carried out 500 epochs with gave a 78.3% accuracy rapidly. The author claims that the model will help in avoiding human error and will not be time consuming as they are the main concern in pill inspection.

Mac [16] proposed an improved Convolutional Neural Network for automatic pill inspection in manufacturing. The author implemented Gauss filtering in the first step, Hog feature extraction in the second step. Lastly, an improved Yolo v3 model was used for online detection of the pill defects. The author claims that the training and validation loss has nearly reduced to 0% which is very impressive. The author believes that this proposal can be very effective.

Lee [17] et al proposed a model to detect pills with limited training data. The authors used various pills of different shapes and colors to achieve the targets. 3D augmentation technique was also implemented to avoid overfitting due to the limited data. 2D rotation and 3D augmentation were used with 20 and 40 types of pills. The author claims that the accuracy of the with 20 types of pills was 99.1% and with 40 types of pills was 94.0% which is impressive.

Chen [18] et al. proposed an automatic pill inspection system using imprint information. It is mostly based on the pill's imprint feature, which is retrieved by the suggested MSWT (modified stroke width transform) and characterized by WSC (weighted shape context). The Authors claim that their method can give an accuracy to 92.03% when trying to classify more than 10,000 pill images in 2000 categories.

Lima [19] et al. proposed an automatic classification system for pill images based on their shape and color. The authors highlighted that pill recognition can reduce the misuse of medication. The authors used image processing techniques by supporting vector machines and Multilayer Perceptron classifiers. The experiment was conducted on data provided by the National Library of medicine. The authors claim that the accuracy was above 99.3%. The result is evidence of the efficiency of the model.

Patel [20] proposed various methods to inspect Pharmaceutical Tablets in diverse environments. The proposal contains deep learning and machine learning methods and presents a comparison between them. The author's model showed promising results such as Global Convolution Network giving a 96% percent. The author believes that this can be implemented in the production and packaging industry.

Qasim [21] et al. proposed an automated system using Artificial Neural Network algorithm to replace manual tablet sorting. The authors highlighted that several flaws in tablets pose a concern in the pharmaceutical industry. Inadequate fines-to-granules ratio, insufficient moisture content, and bad machine settings are some of the causes of visual defects such as flaws in tablet pill covers. The authors claim that the accuracy obtained is 94.4% and the program was done using MATLAB Package.

Tan [22] et al. proposal consisted of three object detection models. The first model was using Retina Net which had Mean Average Precision of 82.89%. The second model, which uses Single Shot Multi-Box Detector (SSD) did not show promising results. The third model was Yolo v3. The Mean Average Precision obtained was 80.69%. However, Yolo v3 had a greater detection speed compared with the other two models and it also worked well on hard samples, but the mean average precision was greater in Retina Net. The author suggested that implementing Yolo v3 model can be more suitable for deployment in hospital equipment. Chen [23] also proposed the same method above. The authors claim that Mean Average Precision of the Retina Net is 87.69%. The SSD did not get a good Mean Average Precision. However, the Yolo v3 model had a Mean Average Precision of 80.17%. Both proposals encouraged the use of yolo v3 due to its detection speed and detection of hard samples.

Xing [24] et al. proposed a smart capsule defection system using neural network. The authors identified that manual sampling has low efficiency, less reliability and high cost. The authors claim that the model is also faster after 150 iterations and the accuracy obtained is above 92.5%. The model can also give accurate results even if the location, size, or any other factor is changed. The authors believe that it can provide technical support for the non-destructive testing of tablets.

Zhu [25] et al. proposed implementing capsule neural network for pill defect recognition. The authors investigated the effects of dynamic routing iteration and different compression functions on small data sets. The model shows that both factors can affect the result. The authors claim that implementing capsule neural network can give more than 90 percent accuracy and the accuracy will improve after each iteration.

Sun [26] et al. proposes a method to detect tablet defects using yolo v3. The author used industrial cameras to collect the defect images in a dataset and used Darknet-53 to extract features. Secondly, used FPN feature and finally used yolo-head to obtain prediction results. The author claims that MAP (Mean Average Precision) obtained is 92.97% which is impressive. The author is quite convinced that this model is very feasible to use.

Galata [27] et al. presented a model in which images were captured from a digital camera. Deep learning is used to identify the coating defects and the coating thickness of the tablets. Yolo v5 was used to detect. There were 5 defective classes. The authors claim the accuracy to be 98.2%. The

authors believe that this technique can look after the screening of the tablets and improve quality control.

Tsai [28] et al. proposed an automatic drug pills detection system. There are two stages of this method. First is detection and the second is classification. The authors have used a deep convolutional neural network to extract features in detection phase. In the classification phase, the pills position output used the pills localization stage. The experiment consists of 400 pills images and 2825 annotations. The author claims that the highest accuracy obtained is 91.8 %.

Han [29] et al. proposed a quality inspection of cherries with the help of Yolo v5. The authors have stated that the manual quality inspection is very time consuming. The authors have emphasized using Yolo v5 as it has higher accuracy, fast speed, and small size. The cherries were extracted by flooding filling algorithm. The authors claim that the accuracy after 20 epochs was 99.6%. This shows that Yolo v5 is very effective with small model training also.

Fujii [30] proposed an automatic inspection of drugs based on computer vision. The authors captured both sides of the medicines and conducted the experiment with 100 naked tablets. The tablets consisted of engraved tablets too. Drug inspection through computer vision is very beneficial as compared to manual as it saves time and money. The author claims to get a 100 percent recognition rate which is impressive.

Summarizing the literature, we get to know that there is a dearth of research that focuses on pill inspection with Yolo v5. However, we can see that a lot of research is being done to solve the pill inspection issue. The main purpose of every research was to save time, save money and get accurate results. Pills are used daily in humans' life, so it is important to discover ways to maintain their quality. Secondly, Reference [16] is the only article which has used yolo v5 for drug inspection. Furthermore, there is a lack of representative data scaling and variance introduction—a fundamental mechanism for countering data scarcity—as is the case for pills inspection, where no open-source data are available.

III. METHODOLOGY

➤ *Data Procurement*
As much research has been carried out on pill inspections, there were ample data sets available online. The dataset utilized for this research consisted of 548 images in its original form. All images were annotated, to provide ground-truth bounding boxes which are a critical component of object detection and a key divergence point from image classification, which does not require object level annotations.

➤ *Data Augmentations*
Data Augmentation is a process of improving the quality of data during the training of the model. Data Augmentation was utilized for increasing the size and variance within the dataset, to provide a more generalized model with respect to the application. Data Augmentation has many benefits such as

it prevents data scarcity, resolves class imbalance in classification and increases generalization ability for the models. However, effective generalization can only be achieved by applying representative augmentations for the given domain. Hence, the applied augmentations were aimed at modelling the production floor environment to accentuate key features within the dataset.

- *Vertical-Sample Component Modelling*
Manufacturing Industries can have production lines set up in different orientations, depending on the location, regulations, and other internal configuration requirements. Not factoring this variance into the model training process via modelled sample generation may lead to false generalization and an ineffective model post deployment. Due to the potential for the abovementioned manufacturing methods to result in variable orientations of the obtained PV cell surface pictures, vertical-sample component was applied to the original dataset, via (1) produce representative samples, as illustrated in Figure 1.

$$f(x,y) = img(H - x - 1, y) \qquad (1)$$

Where img is the original image, (x, y) are the pixel coordinates in the original image, and H is the height of the image.
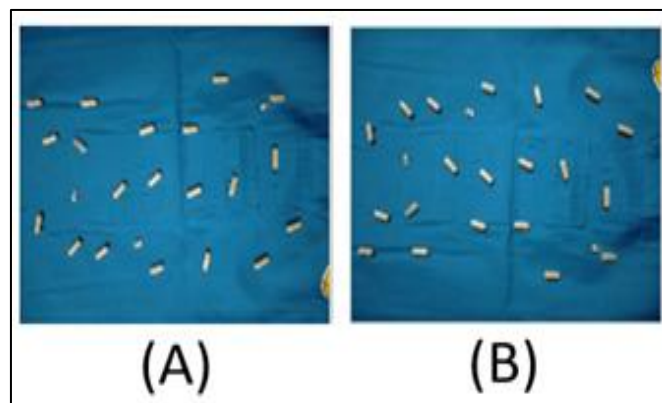

Fig 1 Vertical Augmentation (A) before (B) After

- *Horizontal-Sample Component Modeling*
Additional to the above logic for vertical augmentation generation, the variance from the production floor could also be due to the flexible external device placement angles, i.e., the captured imges would differ in their content similarity based on the orientation of the capturing hardware. Horizontal-sample generation was used to address this variance. For instance, using the "Horizontal" approach on a typical cell image with a roughly uniform surface would replicate the input image because of the symmetrical arrangement of the pills, as expressed in (2).

$$x' = W - x \qquad (2)$$

Where x' = Flipped Horizontal Coordinate. W = Width of the image. X = original horizontal Coordinate.
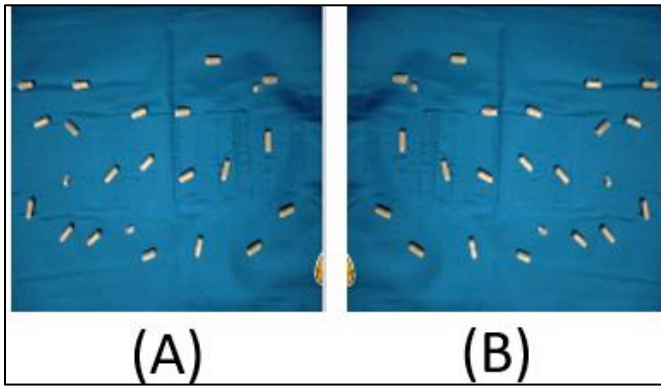
Fig 2 Horizontal Augmentation (A) before (B) After

- *Rotation Augmentation*

The use of Rotation can be seen in Figure 3. Rotation is one of the most useful types of augmentation as it changes the angle at which it can be seen. The purpose of using this augmentation is due to the ground realties i.e., based on the manufacturing facility, production line configuration, the captured samples may be skewed in either direction to varying degrees. This was modelled via (3), with Figure 3 showing a 15 degrees sample.

$$f(x,y) = R * (x - xc) + C * (y - yc) + xc - C * (x - xc) + R * (y - yc) + yc \quad (3)$$

Where img is the original image, (x, y) are the pixel coordinates in the original image, (xc, yc) is the rotation center, and R and C are the sine and cosine of the rotation angle theta, respectively.
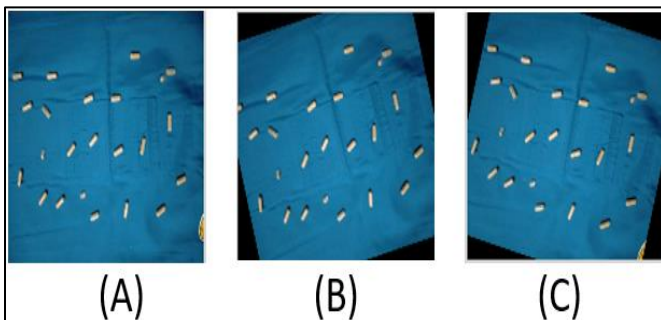

Fig 3 Rotation Augmentation (A) before (B) After -15 (C) After +15

- *Brightness Augmentation*

The use of Brightness can be seen in Figure 4, based on a 10% dark/bright component, as expressed in (4). This was applied to manifest varying LUX intensities with manufacturing facilities. Not catering for this type of variance can have a detrimental impact on the models generalization capacity and effectiveness post deployment, in conditions were the LUX intensity distribution is too low or too high, compared to the training dataset.

$$f(x,y) = img(x,y) + k \quad (4)$$

Where img is the original image, (x, y) are the pixel coordinates in the original image, and k is a scalar value added to each pixel value in the image.
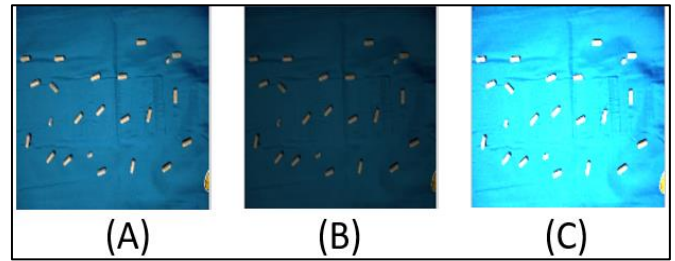

Fig 4 Brightness Augmentation (A) before (B) After -55 (C) After +55

- *YOLO-v5 Architecture.*

Yolo-v5 was selected as the proposed single stage detector, due to its lightweight footprint making it deployable onto constrained edge devices and real-time inference capacity. It has four versions which are small, medium, large, and extra-large. The variants are characterized based on their accuracy and computational complexity with respect to the number of parameters, i.e., Yolo-v5x is the largest variant with the highest accuracy but also computational more demanding compared to Yolo-v5s.

The proposed architecture compromised of 3 distinctive layers with respect to functionality. The first was Backbone, utilized for feature extraction purposes based on the input i.e., training dataset. The second layer was the neck which makes a combination of image features at various scales, aspect ratios before feeding into the subsequent layer. The ultimate component was the 'head' layer providing the prediction functionality based on the data received from the preceding layers. The architecture is presented in Figure 5.

IV. RESULTS

The implementation and design of the architecture was done on Google Collaboratory. The reason for using Google collab was because of its accelerated compute environment which includes GPU and TPU. GPU was used in the training process as the model required a high level of precision. Four experiments were conducted, aimed at manifesting the effectiveness of the modelled augmentations, starting with the original dataset.
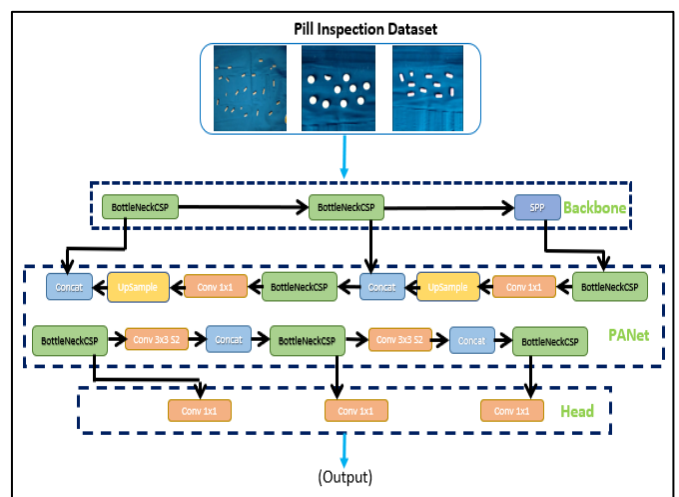

Fig 5 Proposed YOLO v5 Architecture Pipeline for Pill Inspection

➢ *Original Dataset*

The first experiment was conducted with the original number of images. The number of images was 548. As per the training performance presented in Figure 6, it is evident, that the model was not able to generalize on the dataset in the given number of epochs i.e., reaching around 52% MAP at 30 epochs. It may be argued that further increasing the epochs may improve accuracy, however, this would also require further computational cost i.e., GPU usage.
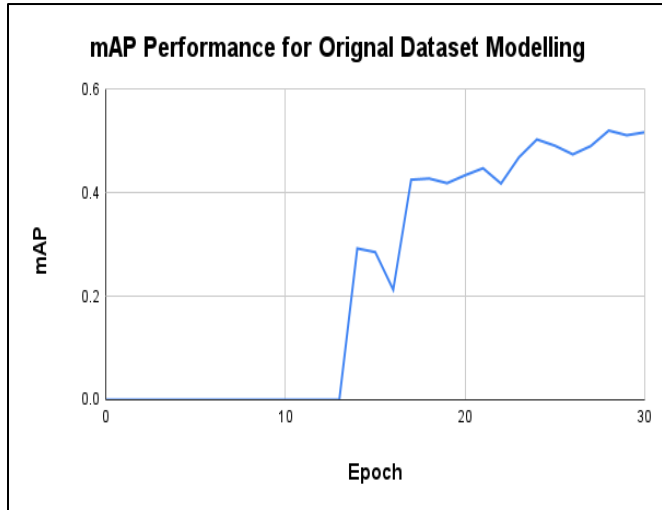

Fig 6 Performance of Original Dataset Modelling mAP @ 0.5

➢ *Data Augmentation with Horizontal and Vertical Augmentation*

The second iteration involved utilizing representative augmentations, in an orderly fashion as demonstrated in the methodology section, starting with the deployment of horizontal and vertical manifestations. The obtained results were notably superior compared to the first experiment i.e., original dataset. The training performance graph reveals a significant improvement, as the mean Average Precision (mAP) at a threshold of 0.5 approached 80% compared to 52% for the original dataset in the same number of epochs. Despite these encouraging outcomes, the aim was to achieve an enhanced performance within a smaller number of epochs, which led to further augmentation exploration.
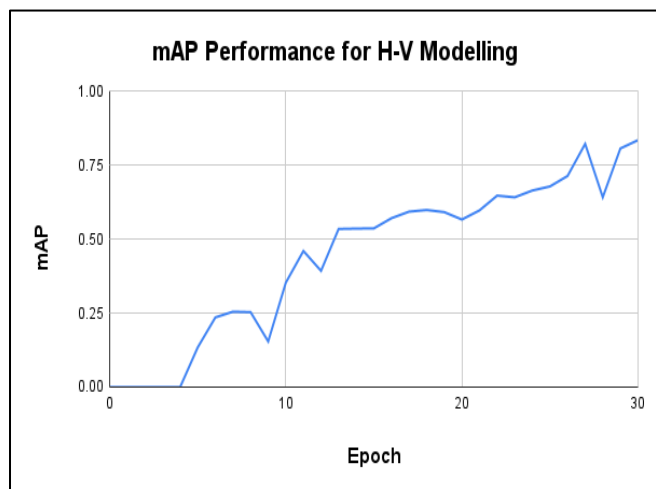

Fig 7 Performance of H-V (H-V Stands for Horizontal and Vertical) Modelling mAP @ 0.5

➢ *Data Augmentation with Horizontal, Vertical and Brightness Augmentation*

The third experiment involved amalgamation of the previous augmentations i.. e, horizontal, vertical with brightness adjustments, based on a brightness range of +/-10 percent. This was aimed at modelling the varying LUX intensities within different manufacturing facilities. The increased number of images provided a better training opportunity for the model. As anticipated, after approximately 30 epochs, the model achieved a mAP at a threshold of 0.5 that was close to optimal (100%), indicating significant improvement compared to previous experiments. While this experiment yielded better results, the last iteration was focused on determining whether convergence could be reached in a lesser number of epochs.
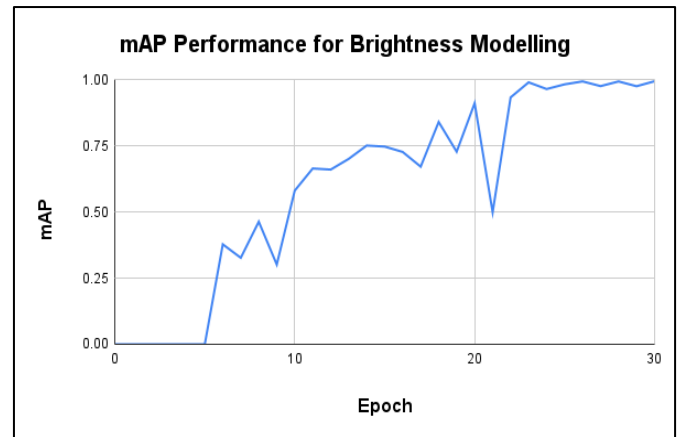

Fig 8 Performance of Brightness Modelling mAP @ 0.5

➢ *Data Augmentation with Horizontal, Vertical, Rotation Brightness Augmentation.*

The fourth experiment involved augmentations such as horizontal, vertical, brightness adjustments of +-10 degrees, in addition to modelling hardware induced variance via rotational adjustments of +/-15 degrees. As evident from Figure 9, this had profound impact on the convergence speed with the model reaching close to optimal performance by the 20th epoch. This demonstrated the efficacy of the proposed augmentations in not only improving accuracy but also reducing convergence time. The latter being an important metric for manufacturing facilities as it involves the use of GPUs for the training process, hence longer training time implies higher computational costs.
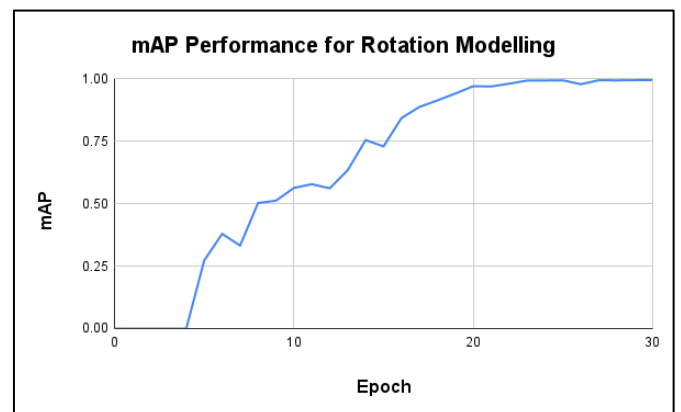

Fig 9 Performance of Rotation Modelling mAP @ 0.5

V. DISCUSSION

The aim of the research was to present an augmentation pipeline that was representative of the ground realities in the pill manufacturing industry. The efficacy of the proposed augmentations was validated via the training of the single stage Yolov5 detector. Yolov5 was selected due to its complementary nature with respect to the production floor realities i.e., it provided a lightweight architecture that could be deployed onto constrained edge devices for real-time inferencing.

As evident from Figure 10, our iterative approach demonstrated the effectiveness of the proposed augmentations in accurately modelling the variance found within manufacturing facilities from varying LUX intensities to hardware induced modifications. Also, to further simulate the production floor realties, Colab was used as the training platform with limited access to GPUs. This was representative of manufacturing facilities that may not have access to large on-site GPUs and hence would require retraining of models on-site with limited computational resources. Comparing the drastic improvement in performance, it can be seen that the original dataset achieved 52% mAP with the globally defined epochs which the final iteration i.e., amalgamation of proposed augmentations was able to achieve almost optimal performance in just 20 epochs, saving on training resources in addition to high accuracy.

VI. CONCLUSION

In conclusion, pill inspection utilizing the YOLOv5 deep learning model yielded encouraging results in accurately recognizing and classifying tablets. When compared to other deep learning models, the usage of YOLOv5 has enabled faster and more efficient picture processing while maintaining excellent accuracy rates. With increased concern about medicine quality and safety, the use of YOLOv5 in pill inspection can assist verify the authenticity and integrity of pharmaceutical products. However, additional research and development are required to improve the model's effectiveness in recognizing and categorizing pills of varying forms, sizes, and colors, as well as to address possible problems such as image distortion and lighting conditions. Overall, YOLOv5 has shown to be a beneficial instrument for pill inspection and quality control in the pharmaceutical industry.

The proposed approach can also be utilized in other edge constrained domains such as quality inspection in renewable energy [31], security [32,33] and the food industry [34].

REFERENCES

[1]. M. Hussain, H. Al-Aqrabi, M. Munawar, R. Hill, and S. Parkinson, "Exudate Regeneration for Automated Exudate Detection in Retinal Fundus Images," IEEE Access, pp. 1–1, 2022, doi: https://doi.org/10.1109/access.2022.3205738.

[2]. "Domain Modelling For A Lightweight Convolutional Network Focused On Automated Exudate Detection in Retinal Fundus Images | IEEE Conference Publication | IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/1018424 4 (accessed Feb. 12, 2024).

[3]. "Custom Lightweight Convolutional Neural Network Architecture for Automated Detection of Damaged Pallet Racking in Warehousing & Distribution Centers | IEEE Journals & Magazine | IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/1014510 4 (accessed Feb. 12, 2024).

[4]. "A Gradient Guided Architecture Coupled With Filter Fused Representations for Micro-Crack Detection in Photovoltaic Cell Surfaces | IEEE Journals & Magazine | IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/9783036 (accessed Feb. 12, 2024).

[5]. "Lightweight Convolutional Network For Automated Photovoltaic Defect Detection | IEEE Conference Publication | IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/1018423 6 (accessed Feb. 12, 2024).

[6]. D. Animashaun and M. Hussain, "Automated Micro-Crack Detection within Photovoltaic Manufacturing Facility via Ground Modelling for a Regularized Convolutional Network," Sensors, vol. 23, no. 13, pp. 6235–6235, Jul. 2023, doi: https://doi.org/10.3390/s23136235.

[7]. M. A. R. Alif, M. Hussain, G. Tucker, and S. Iwnicki, "BoltVision: A Comparative Analysis of CNN, CCT, and ViT in Achieving High Accuracy for Missing Bolt Classification in Train Components," Machines, vol. 12, no. 2, p. 93, Feb. 2024, doi: https://doi.org/10.3390/machines12020093.

[8]. "When, Where, and Which?: Navigating the Intersection of Computer Vision and Generative AI for Strategic Business Integration | IEEE Journals & Magazine | IEEE Xplore," ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/1031629 6 (accessed Feb. 12, 2024).

[9]. H.-J. Kwon, H.-G. Kim, and S.-H. Lee, "Pill Detection Model for Medicine Inspection Based on Deep Learning," Chemosensors, vol. 10, no. 1, p. 4, Jan. 2022, doi: https://doi.org/10.3390/chemosensors10010004.

[10]. T. T. Mac, "Application of Improved Yolov3 for Pill Manufacturing System," IFAC-PapersOnLine, vol. 54, no. 15, pp. 544–549, 2021, doi: https://doi.org/10.1016/j.ifacol.2021.10.313.

[11]. H.-J. Kwon, H.-G. Kim, S.-W. Jung, and S.-H. Lee, "Deep Learning and Detection Technique with Least Image-Capturing for Multiple Pill Dispensing Inspection," Journal of Sensors, vol. 2022, pp. 1–20, Oct. 2022, doi: https://doi.org/10.1155/2022/2339188.

[12]. J. Shen and Q. Wang, "Drug quality re-inspection based on YOLO deep learning," in Proceedings of SPIE, vol. 12287, 2021, article no. 122871R, doi: 10.1117/12.2641004

[13]. L. S. Cordeiro, J. S. Lima, A. I. Rocha Ribeiro, F. N. Bezerra, P. P. Rebouças Filho, and A. R. Rocha Neto, "Pill Image Classification using Machine Learning," IEEE Xplore, Oct. 01, 2019. https://ieeexplore.ieee.org/abstract/document/8923984 (accessed Apr. 04, 2023).

[14]. U. Patel, "Machine Learning-based Pharmaceutical Tablet Inspection and Recognition Techniques – A Review," IEEE Xplore, Mar. 01, 2021. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9396039 (accessed Apr. 04, 2023).

[15]. M. Al-Ani, "Efficient approach of detection and visualization of the damaged tablets," 2018, [Online]. Available: https://www.researchgate.net/profile/Muzhir-Al-Ani/publication/323514989_Efficient_approach_of_detection_and_visualization_of_the_damaged_tablets/links/5adcdcc0aca272fdaf86c5cc/Efficient-approach-of-detection-and-visualization-of-the-damaged-tablets.pdf

[16]. L. Tan, T. Huangfu, L. Wu, and W. Chen, "Comparison of YOLO v3, Faster R-CNN, and SSD for Real-Time Pill Identification," Comparison of YOLO v3, Faster R-CNN, and SSD for Real-Time Pill Identication, Jul. 2021, doi: https://doi.org/10.21203/rs.3.rs-668895/v1.

[17]. L. Tan, T. Huangfu, L. Wu, and W. Chen, "Comparison of RetinaNet, SSD, and YOLO v3 for real-time pill identification," BMC Medical Informatics and Decision Making, vol. 21, no. 1, Nov. 2021, doi: https://doi.org/10.1186/s12911-021-01691-8.

[18]. J. Liu, M. Zhu, T. Cai, D. Kong, and Y. Xing, "Intelligent Tablet Detection System Based on Capsule Neural Network," IEEE Xplore, Jan. 01, 2022. https://ieeexplore.ieee.org/abstract/document/9719182 (accessed Apr. 04, 2023).

[19]. W. He and M. Zhu, "Application of Capsule Network to Tablet Identification," 2021 4th International Conference on Algorithms, Computing and Artificial Intelligence, Dec. 2021, doi: https://doi.org/10.1145/3508546.3508569.

[20]. Y. Sun and S. Shao, "Research on Detection Algorithm of Tablet Surface Defect Based on Yolov3," Academic Journal of Science and Technology, vol. 1, no. 1, pp. 20-25, 2022.

[21]. M. Ficzere et al., "Real-time coating thickness measurement and defect recognition of film coated tablets with machine vision and deep learning," International Journal of Pharmaceutics, vol. 623, p. 121957, Jul. 2022, doi: https://doi.org/10.1016/j.ijpharm.2022.121957.

[22]. Y.-Y. Ou, A.-C. Tsai, J.-F. Wang, and J. Lin, "Automatic Drug Pills Detection based on Convolution Neural Network," IEEE Xplore, Oct. 01, 2018. https://ieeexplore.ieee.org/abstract/document/8705849 (accessed Apr. 04, 2023).

[23]. W. Han, F. Jiang, and Z. Zhu, "Detection of Cherry Quality Using YOLOV5 Model Based on Flood Filling Algorithm," Foods, vol. 11, no. 8, p. 1127, Apr. 2022, doi: https://doi.org/10.3390/foods11081127.

[24]. W. Han, F. Jiang, and Z. Zhu, "Detection of Cherry Quality Using YOLOV5 Model Based on Flood Filling Algorithm," Foods, vol. 11, no. 8, p. 1127, Apr. 2022, doi: https://doi.org/10.3390/foods11081127.

[25]. M. Morimoto and K. Fujii, "A visual inspection system for drug tablets," IEEE Xplore, Oct. 01, 2011. https://ieeexplore.ieee.org/abstract/document/6083822/?casa_token=qU3OTLnJxiEAAAAA:ZVnu4uU5MIzSve7Lt4jNrpDsOdnTaJPwqjAHLxZn0jy19ruL2xDkK6JJPfTYhQP1Gv66cMuBqSpBvW0 (accessed Apr. 04, 2022).

[26]. Medicine, I. of and America, C. on Q. of H.C. in (2000) To Err Is Human: Building a Safer Health System Google Books. [online]. National Academies Press. Available from: https://books.google.co.uk/books?hl=en&lr=&id=Jj25GlLKXSgC&oi=fnd&pg=PT25&dq=+To+err+is+human:+building+a+safer+health+system&ots=bJoasqH0aD&sig=oY7XwUKZMwVlj7iyTL1WXe3HbFk&redir_esc=y#v=onepage&q=To%20err%20is%20human%3A%20building%20a%20safer%20health%20system&f=false [Accessed 5 April 2023].

[27]. of Medicine, "Preventing Medication Errors nap," National Academies Press, 2006, [Online]. Available: https://nap.nationalacademies.org/catalogue/11623/preventing-medication-errors

[28]. M. Liu, Y. Li, L. Li, Y. Shi and D. Huang, "Drug quality re-inspection based on YOLO deep learning," 2021, in Proceedings of SPIE - The International Society for Optical Engineering, vol. 12287, p. 122871R. International Society for Optics and Photonics. doi: 10.1117/12.2641004.

[29]. T. T. Mac and N. T. Hung, "Automated pill quality inspection using deep learning," International Journal of Modern Physics B, vol. 35, no. 14n16, p. 2140050, Jun. 2021, doi: https://doi.org/10.1142/s0217979221400506.

[30]. Y. Hou et al., "A feasibility research on the application of machine vision technology in appearance quality inspection of Xuesaitong dropping pills," Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, vol. 258, p. 119787, Sep. 2021, doi: https://doi.org/10.1016/j.saa.2021.119787.

[31]. M. Hussain, H. Al-Aqrabi, and R. Hill, "PV-CrackNet Architecture for Filter Induced Augmentation and Micro-Cracks Detection within a Photovoltaic Manufacturing Facility," Energies, vol. 15, no. 22, p. 8667, Jan. 2022, doi: https://doi.org/10.3390/en15228667.

[32]. Hussain, M., Al-Aqrabi, H. (2023). Child Emotion Recognition via Custom Lightweight CNN Architecture. In: Yafooz, W.M.S., Al-Aqrabi, H., Al-Dhaqm, A., Emara, A. (eds) Kids Cybersecurity Using Computational Intelligence Techniques. Studies in Computational Intelligence, vol 1080. Springer, Cham. https://doi.org/10.1007/978-3-031-21199-7_12

[33]. T. Alsboui et al., "A Dynamic Multi-Mobile Agent Itinerary Planning Approach in Wireless Sensor Networks via Intuitionistic Fuzzy Set," Sensors, vol. 22, no. 20, p. 8037, Oct. 2022, doi: https://doi.org/10.3390/s22208037.

[34]. M. Hussain, H. Al-Aqrabi, M. Munawar, and R. Hill, "Feature Mapping for Rice Leaf Defect Detection Based on a Custom Convolutional Architecture," Foods, vol. 11, no. 23, p. 3914, Dec. 2022, doi: https://doi.org/10.3390/foods11233914.