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ENHANCING DISTRIBUTION COMPANIES' PERFORMANCE USING DEEP LEARNING TECHNIQUES

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Abstract

In the distribution companies' sector, managing operational expenditures and ensuring efficiency are of utmost importance. With an escalating workload, the sales workforce and its ancillary departments often find themselves stretched, impacting the time and effort allocated to daily tasks and overarching monthly objectives. By leveraging deep learning, there are avenues to alleviate these challenges, potentially leading to reduced effort and costs. This paper unveils a cohesive system that harnesses deep learning methodologies to reduce burdens on sales representatives. Instead of an over-reliance on manual human interventions, the system incorporates deep learning solutions, such as the real-time object detection capability of the YOLO algorithm. Detected objects from images are processed, turned into actionable data, and stored in a MySQL database. Employing Google API, these results are seamlessly transferred from cloud storage to the company's internal servers. The compiled data is then analyzed using a BI tool.

Keywords: Deep Learning, YOLO Algorithm, Efficiency, Distribution companies.

Introduction

Today's economic landscape sees intense competition among distribution companies, especially those specializing in food and other essential commodities. This intense rivalry demands agility and efficiency to ensure superior customer service. One of the primary challenges these companies grapple with is managing operational costs without compromising the performance of their workforce, which forms the backbone of their operations [1], [2].

Introducing new customer service tasks often exacerbates the pressure on teams, from sales to back-office support. With the ever-evolving global market dynamics and the inter-company competitive edge, the sales department often encounters hurdles in meeting annual targets. This scenario can hinder a sales representative's daily objectives, such as customer visits and successful deal closures, leading to potential ramifications in their monthly performance evaluations and escalating task backlogs.

In the sphere of Fast-Moving Consumer Goods (FMCG), ensuring timely product availability amidst fierce competition from numerous brands with similar offerings poses another challenge.

The onus is on the company's leadership to equip their salesforce with the right tools to maintain consistent performance in alignment with the company's vision. Deep learning has emerged as a sought-after solution, aiming to optimize costs and bolster sales efficiency. Several sectors have benefitted from deep learning's cost-reduction capabilities, including its role in enhancing workforce efficiency, as evidenced by studies [1], [2].

For instance, integrating Faster-RCNN object detection techniques in sales tools for grocery settings has been shown to improve sales representatives' productivity while diminishing errors due to work strain [1]. Companies that have embraced artificial intelligence often outpace those reliant on conventional methods, driving profitability and sustainability [2], [3]. Beyond the FMCG sector, AI's cost-saving prowess is evident in institutions like healthcare, underscoring its broader applicability [4]-[6].

Our research indicates that distribution companies firms often overburden sales representatives with continually evolving tasks, affecting their daily outreach plans to retailers. Furthermore, the need for accurate in-store product placements as per planograms and the employment of additional personnel to transcribe these tasks into daily reports places undue pressure on the sales representative and leads to escalated operational costs.

In response to this conundrum, our study leverages the power of deep learning, particularly YOLO V7. Our objective is to alleviate the sales representative's duties without necessitating extra manpower for report generation. The Object Detection System (ODS) we've developed is poised to seamlessly handle these responsibilities, from task inception to report preparation.

RELATED WORK

In [1], a novel system was introduced with the aim to rectify errors and elevate efficiency, subsequently enhancing the productivity of sales representatives. This system harnesses the power of Faster-RCNN algorithms, a deep learning object detection mechanism, to categorize market products. Subjected to multiple conditions in retail settings, the system delivered an impressive accuracy rate of 99%.

[2] detailed an investigation highlighting the positive ramifications of leveraging AI in the FMCG sector, underscoring the potential for cost reduction and heightened performance of sales teams. With the aid of AI-centric techniques and algorithms, the FMCG landscape can extrapolate insights from accrued operational data over extended periods. This strategic foresight can be pivotal in streamlining inventory management, forecasting sales, mitigating unnecessary expenses, and ensuring timely replenishment of retail stocks to satiate consumer demands.

[3] presents evidence suggesting that the amalgamation of ML and AI has emerged as a pivotal ingredient for the success of contemporary sales enterprises. The findings indicate that AI-equipped sales personnel outperform their counterparts. While the study accentuates the indispensability of human intervention in this domain, it also spotlights the augmentation in customer service and improved rapport between consumers and sales representatives facilitated by AI.

In [7], a visionary approach is delineated, advocating the use of scaled-down hardware for real-time identification of vehicles and pedestrians, aiming to curtail mishaps. Anchored in the YOLOv3 deep learning algorithm, this approach offers an economical alternative to the burgeoning costs of advanced driving apparatus. Cost reduction stands paramount in refining ADAS systems for mishap mitigation. This model's prowess in real-time object discernment, amalgamated with NVIDIA series real-time detection, serves as a cornerstone for research pivoted on ADAS and deep learning, especially in domains like real-time traffic analysis, congestion estimation, and mishap detection.

The perpetual quest of Fast-Moving Consumer Goods (FMCG) companies orbits around devising strategies for optimal cost reduction [8]. Drawing from years of steering FMCG enterprises, I've discerned that while numerous outfits in this realm predominantly channel their energies on curtailing expenses, often they do not delve into the repercussions on workforce efficiency. It's an open secret that the sales brigade of FMCG entities forms the linchpin for revenue generation. Hence, any added responsibilities or strategic shifts necessitate robust support mechanisms to retain quality and pare down operational expenditures.

The ascendency of Deep Learning in business spheres to foster informed decision-making is undeniable. Various platforms, including online deep learning paradigms like the YOLO algorithm, have shown promise in the business arena. Our investigation harnesses its capabilities, particularly its real-time object detection prowess, to address tangible challenges in the FMCG sector.

SYSTEM ARCHITECTURE

This section outlines the procedures required to employ deep learning methodologies, with a focus on the object detection framework.

Proposed Methodology

This study introduces an Object Detection System (ODS) as a strategic approach to mitigate cost concerns while enhancing the efficacy of Sales representatives. Leveraging the capabilities of YOLO V7[9]-[12], the system was trained on our specific dataset.

Subsequent to this, the model was tasked with identifying objects in unfamiliar images. The training process was executed on the Google Collab platform[13].

Empirical evidence suggests that the ODS is a potent tool, especially for sales representatives managing extensive stock lists.

Workflow of the Object Detection System (ODS)

The Google Drive API [14] was utilized to retrieve data from images and subsequently transform these findings into accessible formats within the MySQL database [15]. The outcomes were then visualized using Python libraries and Microsoft Power BI [16]. Figure 1 outlines the key procedures involved in our Object Detection System (ODS) setup.

Compilation and Processing the Dataset

Central to our investigation is the capability of the object detection system to recognize an item or multiple items concurrently. To achieve this, it was imperative to amass an adequate number of images representing the target objects. For this purpose, we collaborated with a distribution company, the primary subject of this research.

We obtained a selection of images for seven distinct products from the company to facilitate our analysis. These images were sourced directly from sales outlets in alliance with the sales department. In total, 158 images were amassed. The intent behind limiting the dataset's size was to anticipate potential challenges related to products that might necessitate broader market dissemination by the company.

To ensure richness in our dataset, we prioritized variety in image perspectives and angles. Post-acquisition, image resizing was requisite to align with the input specifications for the YOLO V7 algorithm, which demands an image dimension of (448 × 448).

Subsequent to the resizing activity, all the images were congregated in a singular directory. This enabled the annotation and labeling of the items for training the model. It's also noteworthy that the image files were systematically renamed using a Python script to maintain consistency within our dataset.

Annotation of Objects within Images

Once the images are consolidated in a singular folder and the dataset is primed, we proceed to the pivotal step of annotating objects within these images.

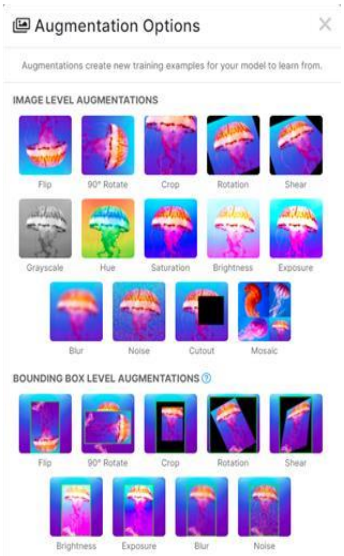
Specifically, we utilized the LabelImg application [17], which facilitates the drawing of bounding boxes around the object and its subsequent labeling. This process results in a TXT file containing numerical representations corresponding to the object group, along with spatial coordinates of the object within the image. These metrics play a crucial role in training our model.

LabelImg was employed for initializing the dataset of the YOLO V7 algorithm, Figure 2 provides a visualization of object annotation using LabelImg.

LabelImg Tool

Preparing the Dataset for Training

Before training, the dataset undergoes preprocessing. Here, image sizes are adjusted for specific algorithms. Data augmentation is essential, utilizing techniques like rotation and scaling. As illustrated in Figure 3, these methods enrich our limited dataset, ensuring more accurate predictions

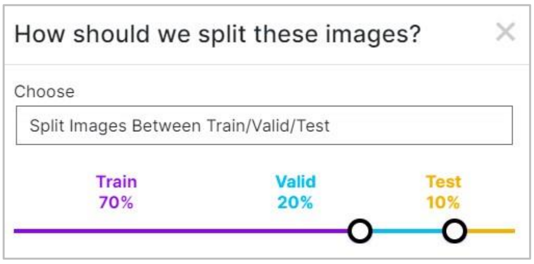


Data Augmentation via RoboFlow

Training and testing the models

Before starting the training process, we must divide the dataset into parts: one for training the model, another for checking the model's efficiency, and the last for testing the model.

Figure 4. shows. For splitting the dataset using the RoboFlow framework, we used the split 70% training 20% validation, and 10% for the test.



Splitting the dataset using RoboFlow

In the coming paragraphs, we will explain the process of training the model and how the results of the model were tested.

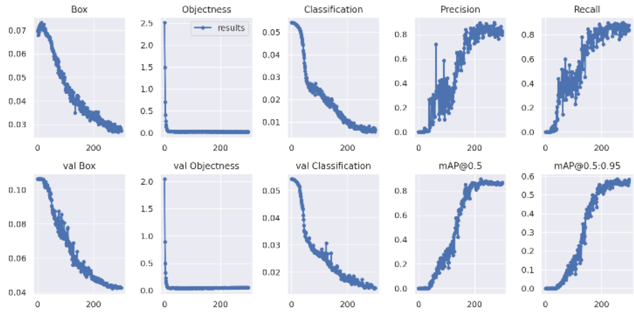
Training The Models: In this step, we use Google Colaboratory (Google Colab) as a platform to prepare the YOLO V7 model to train our dataset on it.

The benefit of using Google Collab is to create a virtual machine (VM) on the cloud, which enables us to use high GPU (Graphic processing unit) and RAM (Random access memory) on Google Cloud. We first need to install the required environment on the virtual machine. First, We need to allow (GPU), which is very important to use when our training dataset contains images, see Figure 5.

```
[ ] import torch
    torch.cuda.memory_summary(device=None, abbreviated=False)
```

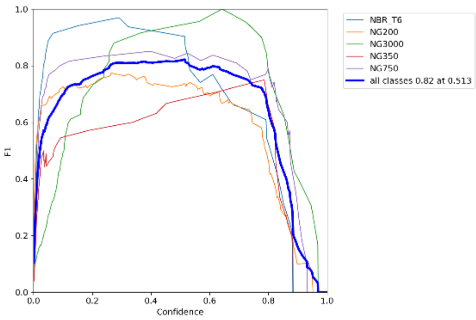
Change MakeFile to have GPU and OpenCV enabled

From Figure 6, our model achieved a mAP of 87% at IoU=0.5 for all classes combined and 59% mAP from IoU=0.5 to IoU=0.95. This accuracy resulted in a 98% rate of material detection on the shelf.



YOLOV7 accuracy and mAP result

From Figure 7. In essence, the model's predictions have a decent balance between precision and recall when we set a threshold of 0.513 for determining matches. The F1 score of 0.82 is a robust indication of the model's performance, especially if it's consistent across various classes.



F1 result

Outcomes from Training: Utilizing YOLOV7 yielded an average IoU of 59% and a mAP of 87%, as depicted in Figure 6. The training completion exhibited a minimized loss and a commendable mAP score. The model's weights, useful for detecting objects in both images and real-time videos, are demonstrated in Figure 8. This illustrates the capability of the YOLOV7 model to identify objects within an image.

YOLOV7 model detection object

RESULTS

Central to our investigation is the enhancement of distribution companies' performance, specifically in terms of expense reduction and sales representative efficiency. Our examination juxtaposed the efficacy of deep learning techniques against the traditional reliance on human-driven processes for specific tasks.

Here, we delineate the financial implications of utilizing deep learning algorithms versus traditional human-centric methods:

Expense Minimization

In the context of human-dependent processes, significant costs accrue from:

Salaries.

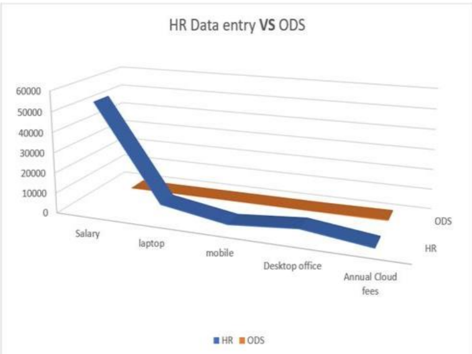
Computer equipment.

Mobile devices.

Offices spaces.

Yearly Cloud services fees.

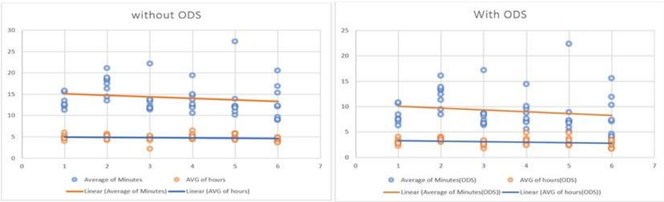
Our analysis revealed that the integration of deep learning techniques resulted in an impressive annual cost reduction of 99%, with an overall expense decrease of 99.99%, as illustrated in Figure 9.



Human vs. ODS Expense Analysis

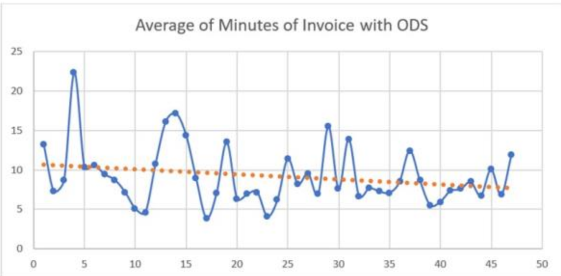
Enhancing Efficiency

T Timely action is pivotal for elevating a sales representative's productivity. The absence of assistive tools can divert a delegate's focus from primary sales activities.
We undertook an on-ground survey with the representatives, monitoring the image collection at various locations, their categorization, and subsequent cloud uploads for backend data analysis. Selected data from representatives across diverse regions indicated that the time required for data organization and cloud upload varies between 7 to 10 minutes.
Hence, the entire duration for generating sales invoices lies between 8 to 27 minutes, as depicted in Figure 10.



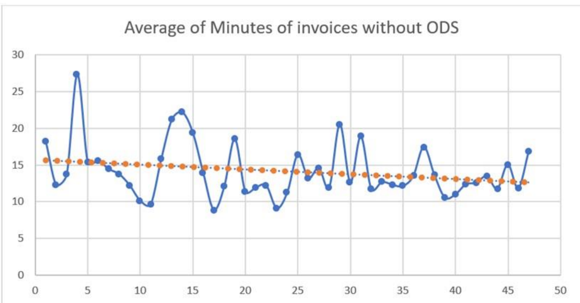
Comparison of Invoice Hours Pre and Post-ODS Implementation

The ODS system trims the time for each bill by approximately 4.5-5 minutes, constituting a 35% reduction for a single invoice originally taking 14.18 minutes. Now, the duration of a representative's visit lies between 3.8 and 22.31 minutes, as depicted in Figure 11.



Invoice Duration Analysis with ODS Implementation

The implementation of the ODS system resulted in an average daily time reduction of 1hr 38 min for the sales representatives, accounting for 28% of the daily route duration. Figure 12 illustrates the time variance before and after deploying ODS.



Time Comparison for Invoicing Pre- and Post-ODS Implementation

The 28% reduction signifies a drop in the average duration a sales representative takes on each invoice to 9.18 minutes. This adjustment allows the sales personnel to incorporate an additional

5 clients into their daily schedule, marking a 21% increase. Consequently, this results in a surge in sales revenue, facilitating a quicker realization of the monthly sales objectives.

CONCLUSION

The transformative potential of deep learning techniques, as evidenced in our study, stands as a testament to its pivotal role in reshaping the operational dynamics of distribution companies. Our exploration into the utilization of the Object Detection System (ODS) presents a compelling case for the tangible benefits these techniques can usher in.

Firstly, the financial metrics alone offer a compelling argument. By transitioning to an automated, deep learning-based system, distribution companies can realize significant cost savings. Our findings indicate that such a shift can result in reducing annual costs by up to 99%, a remarkable figure that underscores the financial viability of adopting such technologies.

Equally important is the increased efficiency in sales representative performance. The traditionally time-intensive tasks of collecting, organizing, and analyzing sales data can be streamlined, saving valuable minutes on each invoice, as our results show. Such time savings not only optimize the daily operations but also afford sales representatives the capacity to expand their client base, further driving revenue.

Furthermore, our findings hint at the scalability and adaptability of deep learning techniques. Not only can they cater to the current demands, but they can also be tailored to accommodate the growing needs of larger operations. This scalability ensures that as a distribution company expands, the deep learning systems in place can grow alongside, ensuring consistent performance enhancements.

In essence, leveraging deep learning techniques, as demonstrated in our study, offers distribution companies a dual advantage of cost efficiency and operational optimization. Such advancements, in turn, not only bolster the bottom line but also pave the way for growth, innovation, and an enhanced ability to meet future challenges head-on. As the realm of deep learning continues to evolve, it will undoubtedly play a central role in driving the next wave of excellence in distribution companies.

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