TEAM BUSINESS INSIGHT REPORT

Introduction

In today's highly competitive retail environment, guaranteeing product availability and optimal shelf display is critical to increasing sales and customer satisfaction. However, maintaining store shelves may be difficult and labor-intensive, including running out of inventory, losing things, and disorganized displays. To tackle these issues, the following business cases explore how to classify store shelf photos into three categories using computer vision techniques, particularly Convolutional Neural Networks (CNNs): "empty shelves," "items in order," and "misplaced items." Improved inventory control, targeted merchandising and increased operational effectiveness are all possible outcomes of the analysis's findings, which can raise profitability.

Business Scenario 1

Following 2021, a series of extraordinary difficulties substantially altered the retail landscape. The ongoing worldwide health crisis, coupled with rising prices and disruptions in the supply chain, sparked a phenomenon that well represented the turbulent times when there were empty shelves in retail establishments throughout the United States. This interruption symbol cost the retail industry $82 billion in missed sales, highlighting how important accurate inventory counts and effective shelf management are to the modern retail industry.

Business Scenario 2

The construction sector has experienced difficulties recently, which have been made worse by the growing calls for lower costs and quicker completion schedules. Conventional building progress tracking techniques, which mostly depend on physical work and visual inspections, have shown to be labor-intensive and prone to human error. There is an immediate need for creative solutions because this inefficiency not only lengthens project schedules but also has a major negative influence on budgetary allocations.

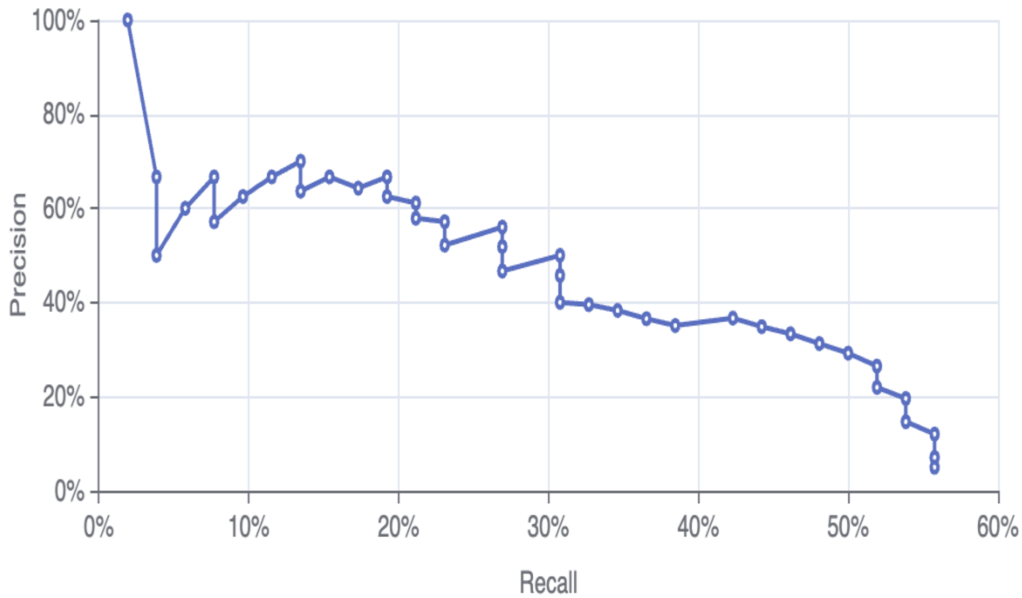
Our Analysis

Using computer vision techniques, our team started a project to tackle these issues in the retail industry. Our goal was to categorize 156 photos from different retail locations, such as Target, Walmart, Safeway, and others, into three different groups: "empty shelves," "items in order," and "misplaced items." The goal of this classification was to represent how retail shelf arrangement and inventory control are now done. After the collection, Convolutional Neural Networks (CNNs) were used to complete the classification task in Dataiku, and the photos were carefully labeled, verified, and inputted. Our model's initial performance score of 0.421 showed how difficult it would be to reliably discern between the given categories based only on the visual data that was given.

Model Performance

The model's average accuracy (AP) over five epochs is shown in the first graph for the training set (green) and the validation set (blue). The model appears to be efficiently learning from the training data, as evidenced by the graph, which shows that the model's precision on the training set grows over the course of epochs. The training and validation sets' loss values are displayed in the second graph. A significant drop in the training loss indicates that the model is learning well. The validation loss, however, does not exhibit a steady decline; rather, it peaks at epoch 2 and then somewhat rises. The model's object detection score was 0.421. The improvement in average precision on the training set indicates that the chosen model is learning, which is encouraging.

Precision-Recall

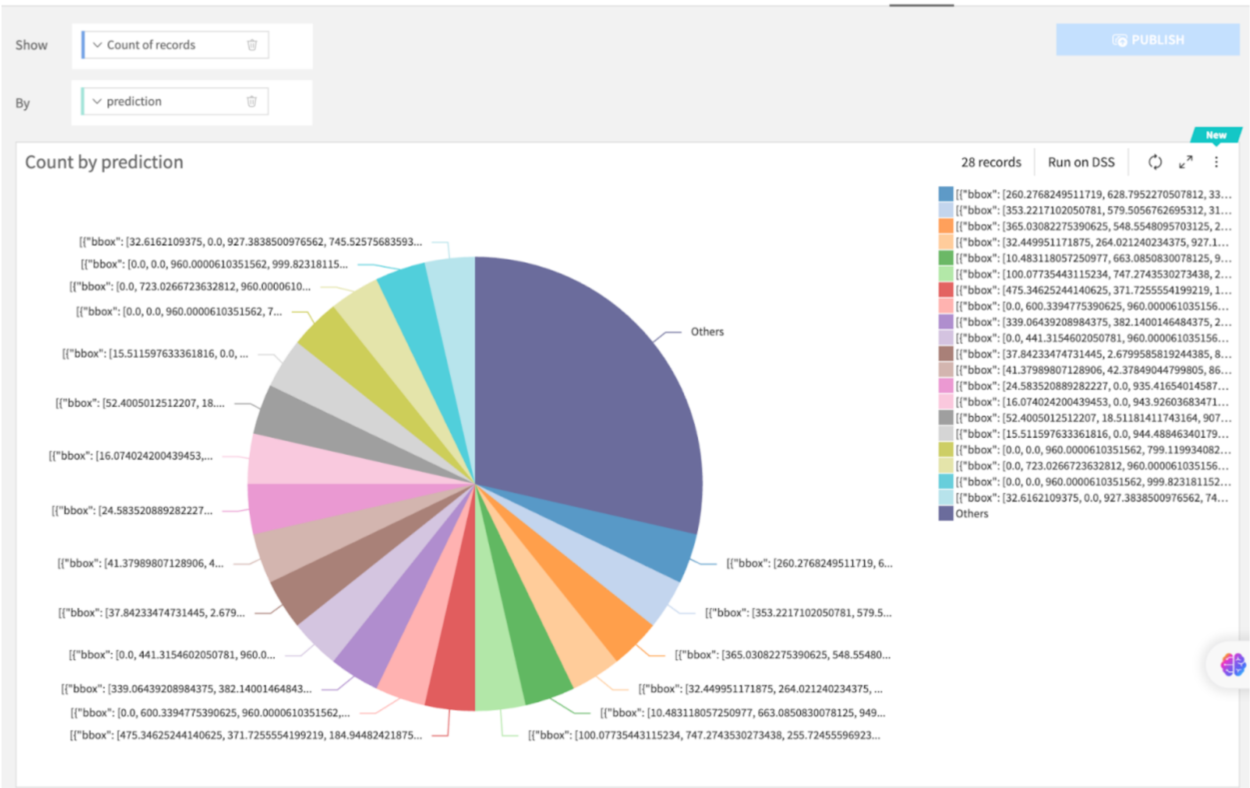


A Precision-Recall (PR) curve is a widely used tool for assessing a model's performance in tasks like binary classification or object detection, especially in cases when the number of examples between the classes is unbalanced. The precision is highest toward the left-hand side of the curve and rapidly decreases as recall rises. This suggests that the model can accurately identify a limited number of positive examples when it is configured to be very selective, striving for very high precision. The model finds more positive instances (greater recall) as we move right along the curve, but the precision drops.

Confusion matrix IOU 0.5 1 0.50

Ground Truth \ Predicted	Items in Order	Misplaced Items	Empty Shelves	Not Detected
Items in Order	8	0	0	19
Misplaced Items	0	7	0	7
Empty Shelves	0	0	7	4
Not an object	29	9	2	0

A thorough analysis of the model's predictions in relation to the true labels (Ground Truth) is given by the confusion matrix. Eight instances of "items in order" were successfully identified by the model, however 19 examples were missed and were marked as "not detected." This implies that although the model can identify certain instances in which items are out of order, a sizable portion of false negatives occur when the model is unable to identify ordered objects. Within "misplaced items," the model has identified seven cases with accuracy. It has, however, also mistakenly labeled seven cases as "not detected," suggesting that the model's sensitivity for identifying misplaced objects may be increased. With "empty shelves," the model appears to function reasonably well, but there are still problems with false negatives. The confusion matrix exhibits a somewhat balanced performance in terms of the classes it can identify, yet it frequently fails to identify items that are supposed to be identified.



Based on bounding box coordinates, the object detection model's predictions are distributed in the Dataiku pie chart. The bounding box coordinates predicted by the model correspond to specific objects detected in pictures, and each slice of the pie represents a distinct collection of these coordinates. The range of slices shows that the model has predicted a great deal of diverse things. Bigger slices indicate more predictions with the same bounding box coordinates, which suggests that the model is biased toward these predictions or that these scenarios or objects appear more frequently in the dataset. The "Others" portion suggests that there are a lot of less common forecasts. Because of their low frequency, these are clustered together.

Frameworks Used

Localization and Convolutional Neural Networks (CNNs) for image detection, together with Dataiku's platform's analytical capabilities, have presented us with actionable insights. CNNs can precisely locate products on store shelves in addition to categorizing photos into groups like "empty shelves" or "misplaced items." This dual ability is essential for streamlining and automating inventory control, which has a direct impact on our business plan to maximize shelf space and improve customer satisfaction. We can evaluate and comprehend the model's efficacy and precision in identifying and correctly positioning items in a retail setting thanks to Dataiku's visual tools. These insights which are illustrated by confusion matrices and precision-recall curves are crucial for helping decision-makers decide whether to adopt and fund computer vision systems to optimize retail operations.

We can apply statistical measures such as TF-IDF (Term Frequency-Inverse Document Frequency) to text analytics in our retail data. By emphasizing the most pertinent terms, TF-IDF assists in comprehending the meaning of words or terms in product descriptions and customer feedback. Through the analysis of product details and customer reviews, this approach enhances our CNN insights by providing a deeper understanding of consumer preferences and market trends. Dataiku's all-inclusive platform, CNN's visual analytics, and TF-IDF's text analysis combine to offer a powerful collection of capabilities that impact our business choices. These include keeping inventory levels optimal, setting up shelves in accordance with customer behavior, and anticipating and acting upon new trends in retail.

Conclusion

Our extensive research, which made use of Dataiku's Convolutional Neural Networks and sophisticated computer vision techniques, has given us a comprehensive understanding of the model's present capacity for retail shelf image classification. The model's performance evaluation indicated a promising learning curve, particularly with regard to average precision gains during the training stage. While our project has made great progress in using CNNs for retail shelf analysis, it has also revealed how difficult it is to classify complicated real-world data. The knowledge gained from this research will form the basis for further improvements as the retail industry changes and we strive to achieve more precision and dependability in inventory management through artificial intelligence.

The versatility of CNN technology and our model can significantly benefit sectors such as healthcare, agriculture, and urban planning, in addition to construction and surveying. In healthcare, it can improve diagnostic accuracy through image analysis, while in agriculture, it enhances crop monitoring and disease detection, and in urban planning, it aids in spatial analysis and infrastructure development.

Bibliography

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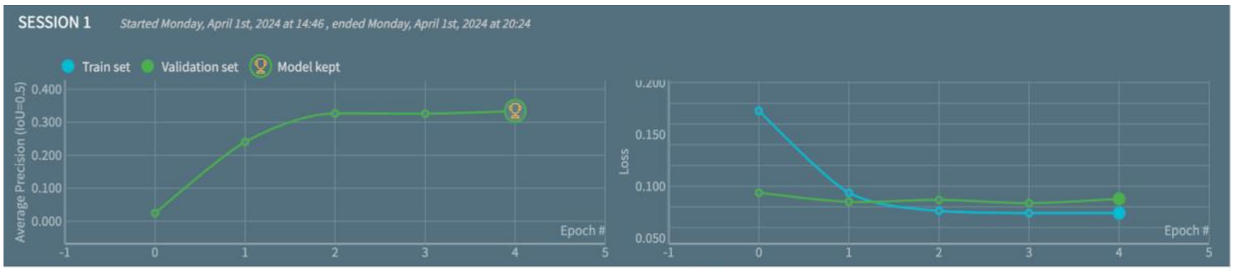
Klein, E. (2023, February 5). Opinion | The Story Construction Tells About America's Economy Is Disturbing. The New York Times. https://www.nytimes.com/2023/02/05/opinion/economy-construction-productivity-mystery.html

Appendix



Object detection (s1) 0.421 ✓ Done 6 days ago (2024-04-01 20:24:15) Diagnostics (2)

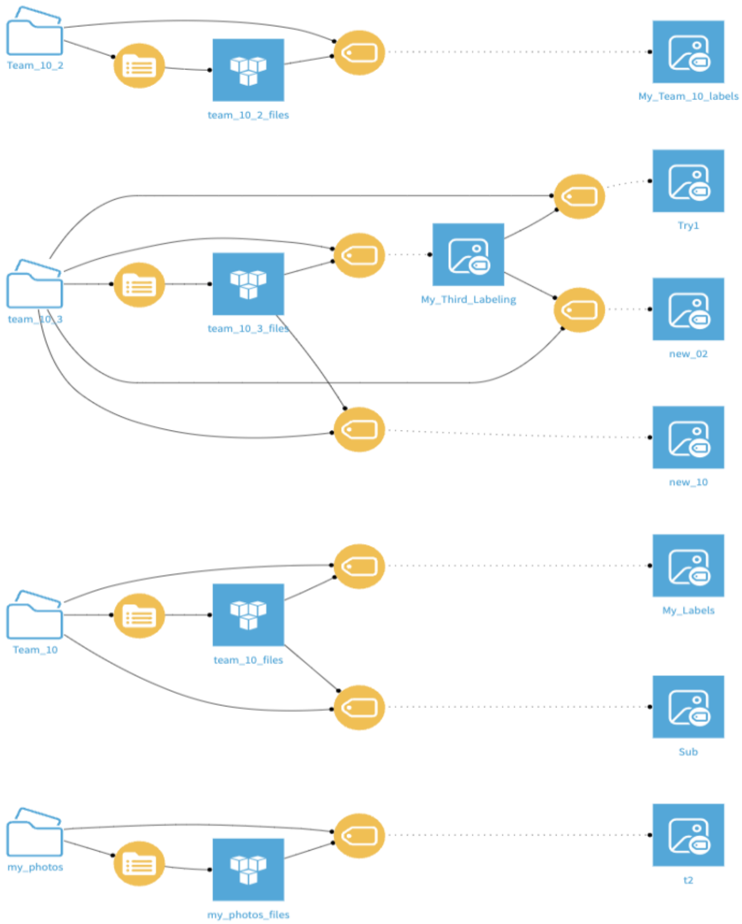
No model-specific details available.

Train set	128 rows
Test set	28 rows
Train time	5 hours and 37 minutes

Performance metrics

Filter class...

	Average Precision (IoU=0.5)	Average Precision (IoU=0.75)	Average Precision (all IoUs)
All classes	**0.4213**	**0.1621**	**0.1804**
Items in Order	**0.1661**	**0.0745**	**0.0604**
Misplaced Items	**0.4555**	**0.0159**	**0.1435**
Empty Shelves	**0.6424**	**0.3960**	**0.3372**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