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Application of Computer Vision for Customer Insights: Demographics and Visit Duration in Coffee Shops

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Abstract

The coffee shop industry is increasingly competitive, requiring business owners to adopt data-driven strategies rather than rely solely on intuition, as traditional approaches such as surveys and manual observation are often subjective, time-consuming, and lack scalability. This study aims to design, implement, and evaluate an end-to-end intelligent system based on computer vision to automatically and non-intrusively analyze customer demographics (age and gender) and visit duration (dwell time). The proposed framework emphasizes both technical accuracy and privacy-by-design principles, where facial data is processed in real time without storage, and only anonymized metadata is utilized for business analysis. Using a simulated 60-minute test video containing 50 virtual customers with balanced gender, varied age groups, and predetermined visit durations, the system was evaluated and demonstrated strong performance, achieving 96% accuracy in gender classification, 89% in age group classification, and a Mean Absolute Error of less than 45 seconds in dwell time measurement. The findings confirm that the ethical application of computer vision can provide valuable business insights, including the identification of demographic-based peak hours, the recognition of product preferences, and the optimization of spatial layouts, ultimately enabling coffee shops and Small and Medium sized Enterprises to enhance competitiveness and profitability through data-driven decision-making.

Keywords

Coffee Shop Industry, Customer Analytics, Data-Driven Decision Making.

1. Introduction

Amidst the rapid expansion of the global coffee shop industry, competition has intensified significantly (Kumar et al., 2024). To remain competitive and achieve sustainable growth, business owners can no longer depend solely on intuition (Wang, 2023; Zuo et al., 2022). Instead, data-driven decision-making has emerged as a strategic necessity. A clear understanding of customer profiles specifically who they are, when they visit, and how long they stay represents three fundamental dimensions of consumer behavior analysis (Abadi et al., 2016; Tang, 2016). These insights play a direct role in shaping staff management, marketing strategies, inventory planning, and even the design of spatial layouts (Zhang et al., 2016). Traditionally, such data has been obtained through surveys, loyalty cards, or manual observation (Sandler et al., 2018; Zhichao Lu et al., 2020). However, these conventional methods are often constrained by considerable drawbacks: they are time-consuming, costly, prone to both respondent and observer bias, and typically limited to a small sample of the overall customer base (Pandi et al., 2022).

Computer Vision, a subfield of Artificial Intelligence (AI) that enables machines to perceive and interpret the visual environment, provides a solution that is robust, objective, and highly scalable (Baig et al., 2020; Watson, 2022). Through the use of video footage captured from existing cameras, intelligent systems are capable of automatically extracting demographic information such as age and gender and precisely calculating customer visit durations (Bewley et al., 2016; Vayadande et al., 2024). Despite the maturity of this technology, its adoption within Small and Medium-Sized Enterprises (SMEs), including coffee shops, remains relatively limited. The primary barriers to implementation include high costs, technical complexity, and, most critically, concerns surrounding ethics and data privacy. Addressing this gap forms the central aim of the present study (Yang et al., 2011).

Research on customer analysis through computer vision has advanced significantly in recent years. Initial studies primarily concentrated on people counting as a means of estimating crowd density (Chong et al., 2016; Limna et al., 2021). Later developments expanded into demographic analysis, with numerous Convolutional Neural Network (CNN) models demonstrating strong performance in gender classification and age estimation based on facial images (Bewley et al., 2016). Models such as VGG-Face and MobileNet, in particular, have shown high levels of accuracy and effectiveness for these tasks (Heaton, 2018; Wirsansky, 2020). In relation to dwell time analysis, object tracking algorithms play a central role (Antipov et al., 2017; Kemmer et al., 2022). Traditional approaches, including the Kalman Filter and Hungarian Algorithm integrated within the Simple Online and Realtime Tracking (SORT) framework, provide computational efficiency (Ismail & Malik, 2022; Nithya et al., 2022). More advanced techniques, such as DeepSORT, incorporate deep learning features to enhance tracking accuracy and robustness, particularly in challenging scenarios involving occlusion (Papadopoulos, 2021; Seymour et al., 2022).

Despite significant progress, much of the existing research has primarily concentrated on enhancing algorithmic accuracy using benchmark datasets, with comparatively little attention given to the development of practical, end-to-end systems tailored for business applications (Chen et al., 2022; Kumar, 2022). In addition, ethical and privacy considerations are frequently treated as secondary concerns rather than central elements of system design (Wieder & Ossimitz, 2015; Richards et al., 2019). This creates a notable research gap in the literature, namely the absence of a comprehensive framework that integrates detection, classification, and tracking, while simultaneously transforming technical outputs into actionable business insights and embedding privacy as a foundational design principle (Cavoukian, 2010; Pagallo, 2020).

2. Literature Review

2.1. Demographic Analysis in Retail Using Computer Vision

Demographic analysis, encompassing age and gender classification, is vital for retail businesses like coffee shops to gain insights into customer profiles and enhance decision-making. Computer vision, particularly Convolutional Neural Networks (CNNs), offers high accuracy for these tasks, enabling non-intrusive data collection. Kumar et al. (2024) developed a deep learning model for face-based age and gender classification, demonstrating robust performance across diverse environments, which supports the need for scalable, objective customer analytics. This approach reduces reliance on traditional methods like surveys, which are often subjective and time-consuming. By leveraging CNNs, coffee shops can efficiently analyze customer demographics, informing strategies for staffing, marketing, and layout optimization. Such techniques align with the demand for data-driven decision-making in competitive retail settings, providing actionable insights to improve customer experience and profitability while maintaining efficiency and scalability in real-world applications.

Similarly, Pandi et al. (2022) used CNNs for emotion and gender classification, reporting precision levels above 90%, supporting the feasibility of real-time applications in busy settings. Bewley et al. (2016) integrated tracking with demographic models in their Simple Online and Realtime Tracking (SORT) framework, enabling efficient gender detection amid occlusions. Vayadande et al. (2024) applied similar methods to track barista productivity and customer demographics in coffee shops, demonstrating 95% accuracy in gender estimation, which mirrors the high performance needed for SME adoption. These studies highlight CNN models like MobileNet and VGG-Face as effective for scalable, accurate classification (Sandler et al., 2018; Heaton, 2018; Hermina & Fauziah, 2022).

2.2. Dwell Time Estimation in Computer Vision Systems

Dwell time estimation, which measures customer visit duration, utilizes object tracking algorithms to deliver behavioral insights for optimizing retail operations. Traditional methods, such as the Kalman Filter in the SORT framework, provide efficient real-time tracking with minimal computational demands (Bewley et al., 2016). Advanced approaches like DeepSORT enhance accuracy in occluded scenarios by integrating deep learning features, achieving a Mean Absolute Error (MAE) below one minute for dwell time estimation (Papadopoulos, 2021; Veronica et al., 2025). Similarly, Ismail and Malik (2022) applied computer vision for real-time inspection in agriculture, adapting tracking to dynamic environments, which mirrors retail challenges like fluctuating customer flows. These techniques enable coffee shops to analyze visit patterns, supporting strategic decisions on staffing, layout, and customer engagement, thereby enhancing operational efficiency and competitiveness in dynamic retail settings.

Nithya et al. (2022) used CNNs for defect detection with precise timing metrics, supporting dwell time calculations in crowded spaces. Privacy-by-design is critical to address ethical concerns; Cavoukian (2010) emphasized anonymizing data to prevent storage of sensitive biometrics, ensuring only metadata is used. Pagallo (2020) discussed legal limits of privacy in AI, advocating real-time processing to build trust. Wieder and Ossimitz (2015) linked business intelligence tools with ethical data handling, reducing risks in customer analytics. Richards et al. (2019) analyzed BI effectiveness, stressing privacy to enhance corporate performance. These approaches align with developing systems that balance accuracy, like sub-45-second MAE, with ethical safeguards for SME applications in coffee shops.

3. Methods

To address the research objectives, this study develops an intelligent system designed with a modular architecture. The system records and organizes anonymous metadata for each detected customer, capturing key information such as a unique tracking ID, entry and exit timestamps, visit duration, gender, and estimated age group. For instance, one record corresponds to a young adult male who stayed in the coffee shop for approximately 26 minutes, while another entry represents an adolescent female with the longest recorded stay of around 41 minutes. Another example includes an adult male who remained for about 17 minutes. This structured data collection allows the intelligent system to analyze customer behavior patterns without compromising individual privacy. This metadata illustrates how the system automatically translates raw video input into structured, anonymized information that can be used for business analysis, such as identifying customer demographics, understanding visit patterns, and correlating dwell time with customer segments.

The data indicates that individuals identified with Tracking ID 102, who are female, recorded the longest duration of activity at nearly 3000 seconds. Meanwhile, male participants with Tracking IDs 101 and 103 showed shorter durations, approximately 2000 seconds and 1000 seconds, respectively. These results suggest a noticeable difference in activity duration between genders, with female participants tending to engage in longer activity periods than their male counterparts. Tracking ID 102, corresponding to an adolescent female, recorded the longest stay duration, significantly exceeding those of the male customers represented by Tracking IDs 101 and 103. This visualization complements the metadata shown in Table 1 by providing an intuitive means of identifying patterns and outliers in customer behavior. By linking demographic information with dwell time, the chart enables business owners to observe which customer segments tend to stay longer quickly and, consequently, may engage more with the coffee shop's offerings. Such insights are particularly valuable for strategic decision-making, including staff allocation, marketing campaigns, and layout optimization.

The evaluation of the proposed system was carried out in two main dimensions: the accuracy of demographic classification and the accuracy of visit duration estimation. To measure performance, four standard metrics were employed accuracy, precision, recall, and Mean Absolute Error (MAE). MAE was vital for evaluating dwell time measurement, as it represents the average absolute difference between actual and predicted visit durations, regardless of whether the estimates were higher or lower than the ground truth. A smaller MAE value, therefore, indicates that the system's estimations are closely aligned with reality. The other three metrics, Accuracy, Precision, and Recall, were derived from the confusion matrix, which is built upon four components: True Positives, True Negatives, False Positives, and False Negatives. Accuracy reflects overall correctness, Precision measures the reliability of positive predictions, and Recall evaluates the system's ability to detect all actual positive cases. Taken together, these metrics provide a comprehensive framework to assess the robustness and effectiveness of the system in both demographic classification and behavioral tracking.

4. Results

To ensure evaluation could be conducted without relying on sensitive real-world data, the study employed a dummy dataset specifically designed for testing purposes. The dataset consisted of a 60-minute simulated video created from digital assets to replicate typical customer activity in a coffee shop during peak hours. Within this simulation, a total of 50 virtual customers were modeled, equally divided between 25 males and 25 females, with age groups distributed across four different categories. Each customer was assigned a predetermined visit duration ranging from 5 to 45 minutes to reflect realistic behavioral patterns. Furthermore, the dataset incorporated controlled complexity scenarios, including minor occlusions caused by overlapping customers and variations in lighting conditions, to better approximate real-world challenges faced by computer vision systems.

The formulas applied in this study are derived from the four essential components of the confusion matrix. Prior to presenting the main equations, it is necessary to define these components within the context of the present case, specifically, gender classification, where the category "Female" is designated as the positive class. Based on these definitions, the formulas for Accuracy, Precision, and Recall are introduced to evaluate the system's classification performance.

Accuracy measures how often the model makes a correct prediction across the entire dataset.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{TP+TN}{TP+TN+FP+FN}$$

Table 1. Evaluation Results for Demographic Classification

Metric	Gender Classification	Age Group Classification
Accuracy	96.0% (48/50)	89.1% (43/50)
Precision	0.96	0.88
Recall	0.96	0.89

Table 1 presents the evaluation results for gender classification, showing that the system achieved an accuracy of 96.0% (48 out of 50). This indicates that from a total of 50 customers, the system correctly identified the gender in 48 cases, whether classifying males as male or females as female. Furthermore, the high recall score highlights the system's effectiveness in detecting nearly all positive instances, with only a small number of cases missed.

$$\text{Precision} = \frac{TP}{TP+FP}$$

For gender classification, the system obtained a precision score of 0.96, meaning that 96% of the customers predicted as female were indeed female. Such a high precision value demonstrates the system's strong reliability in producing correct positive predictions.

Table 2. Evaluation Results for Visit Duration Measurement

Metric	Value
Number of Tracked Customers	49 / 50 (98%)
Mean Absolute Error (MAE)	43.7 seconds
Average Actual Duration	22.5 minutes
Average Measured Duration	21.9 minutes

Table 2 summarizes the evaluation results for visit duration measurement. The system successfully tracked 49 out of 50 customers (98%) with a Mean Absolute Error (MAE) of 43.7 seconds. The average actual duration of customer visits was 22.5 minutes, while the system's measured average was 21.9 minutes, indicating a close alignment between estimated and real values.

$$\text{Recall} = \frac{TP}{TP+FN}$$

In gender classification, the system achieved a recall value of 0.96, indicating that it successfully identified 96% of all actual female customers in the dataset. To further support the evaluation process, several variables were defined for use in the formulas.

Here, N_{total} represents the total number of customers in the test data, which in this case is 50, while $N_{tracked}$ refers to the number of customers accurately tracked by the system from entry to exit, totaling 49. For each individual customer *i*, D_{actual} denotes the true visit duration, serving as the ground truth, whereas $D_{measured}$ represents the visit duration estimated by the system for the same customer.

The number of tracked customers serves as an indicator of the system's reliability in monitoring individuals. Rather than being derived from a single formula, this metric is calculated by comparing the number of customers successfully tracked with the total number of customers present in the dataset. The result is generally expressed as a percentage to provide a clear measure of tracking performance.

$$\text{Tracking Rate (\%)} = \left(\frac{N_{\text{tracking}}}{N_{\text{total}}}\right) \times 100\%$$

Application to Your Data:

$$\left(\frac{49}{50}\right) \times 100\% = 98\%$$

The average actual duration represents the mean value of customer visit times obtained from the ground truth dataset. This metric functions as a benchmark or reference standard against which the system's estimated results can be compared, allowing an assessment of how closely the measurements reflect real customer behavior.

$$\overline{D_{\text{actual}}} = \frac{1}{N_{\text{total}}} \sum_{i=1}^{N_{\text{total}}} D_{\text{actual}_i}$$

The sigma symbol ($\sum$) is used in this formula to represent the total sum of a set of values, in this case, the "actual duration for each customer." Specifically, the formula indicates that the actual durations of all customers should be summed and then divided by the total number of customers. According to the data from the previous table, the average actual duration (D_{actual}) is recorded as 22.5 minutes, while the total number of customers (N_{total}) is 50, noting that 49 out of 50 customers were tracked. The application of this formula essentially serves as a reverse process to demonstrate how the 22.5-minute average was derived. The key components of the formula include D_{actual}, which is the average duration to be verified; N_{total}, which serves as the denominator in the calculation; and $\sum_{i=1}^{N_{total}} i\ D_{actuali}$, the most critical element, represents the total sum of actual durations for each customer, from the first to the last. By summing all individual durations and dividing by the total number of customers, the total actual duration can be accurately calculated. Although individual duration data is unavailable, we can determine the total by using the existing average values.

Total Actual Duration = Average Actual Duration × Total Number of Customers

Total Actual Duration = 22.5 minutes × 50 = 1125 minutes

Therefore, the value of $\sum_{i=1}^{N_{total}} i\ D_{actuali}$ is 1125 minutes. This means that if you were to sum the duration of stay for each of the 50 customers, the result would be 1125 minutes.

The duration we have calculated into the initial formula to prove the calculation.

$$\overline{D_{\text{actual}}} = \frac{1}{50} \times \left(D_{\text{actual}_1} + D_{\text{actual}_2} + \cdots + D_{\text{actual}_{50}}\right)$$

$$\overline{D_{\text{actual}}} = \frac{1}{50} \times (1125 \text{ minutes})$$

$$\overline{D_{\text{actual}}} = 22.5 \text{ minutes}$$

This implementation demonstrates that the 22.5-minute value in the table is the result of summing the total actual visit duration of the 50 customers (which totals 1125 minutes) and then dividing it by the number of customers. The 22.5-minute value is the result of this calculation on your ground truth data.

The Average Measured Duration refers to the mean visit time produced by the system's estimations. This metric reflects the central tendency of the calculated results, indicating how the system represents overall customer visit durations.

$$\overline{D_{\text{measured}}} = \frac{1}{N_{\text{tracker}}} \sum_{i=1}^{N_{\text{tracker}}} D_{\text{measured}_i}$$

The key data points include an average measured duration ($D_{measured}$) of 21.9 minutes and a total of 49 tracked customers ($N_{tracker}$). This implementation illustrates how the final average of 21.9 minutes was derived from the individual measurements recorded by the system. The main components of the formula are $D_{measured}$, representing the final average duration, $N_{tracker}$, which denotes the number of data points being averaged, and $\sum_{i=1}^{N_{\text{total}}} i\ D_{measured}$, the core calculation that sums the measured duration for each successfully tracked customer from the first to the last. Although the individual data points for each of the 49 customers are not available, the total measured duration can be determined by reversing the formula: multiplying the average measured duration by the number of tracked customers, resulting in a total of 21.9 minutes × 49 = 1,073.1 minutes. This calculation indicates that the summation component, $\sum_{i=1}^{N_{\text{total}}} i\ D_{measured}$, equals 1.073.1 minutes. Substituting this total back into the original formula confirms how the average of 21.9 minutes was obtained.

$$\overline{D_{\text{actual}}} = \frac{1}{49} \times \left(D_{actual_1} + D_{actual_2} + \cdots + D_{actual49}\right)$$

$$\overline{D_{actual}} = \frac{1}{49} \times (1073.1 \text{ menites})$$

$$\overline{D_{\text{actual}}} = 21.9 \text{ menites}$$

This confirms that the 21.9 minutes listed in your results is the average of the visit durations measured by your system for the 49 customers it successfully tracked. The Mean Absolute Error (MAE) serves as the key metric for evaluating the accuracy of the system's visit duration estimation. It represents the average absolute difference between the durations predicted by the system and the actual ground truth values, thereby providing a clear indication of how closely the estimated results align with reality.

$$\text{MAE} = \frac{1}{N_{\text{tracked}}} \sum_{i=1}^{N_{\text{tracked}}} \left| D_{\text{actual}_i} - D_{\text{tracked}_i} \right|$$

The notation |...| denotes the absolute value, meaning that the difference between the actual and the estimated duration is always treated as a positive number. This is essential, as the focus lies on the magnitude of the error rather than whether the system overestimated or underestimated the visit time. Accordingly, the MAE formula requires calculating the difference between actual and measured durations for each tracked customer, converting each difference into a positive value, summing all these values, and then dividing by the total number of tracked customers. In this study, with 49 customers successfully tracked, the process resulted in a Mean Absolute Error (MAE) of 43.7 seconds, reflecting the average deviation of the system's predictions from the true visit durations.

The components of the MAE formula can be explained as follows. The final result of the calculation is an MAE of 43.7 seconds, obtained from $N_{tracked}$, which represents the 49 customers successfully monitored. The summation term, expressed as $\sum_{i=1}^{N_{total}} i|D_{actuali} - D_{measured}|$ constitutes the core of the formula. It requires calculating the difference between the actual and the estimated visit duration for each tracked customer, converting the difference into an absolute (positive) value, and then adding all of these values together.

The total sum of absolute errors can be obtained by applying the reverse of the MAE formula. Specifically, the Mean Absolute Error (43.7 seconds) is multiplied by the number of tracked customers (49), resulting in a total error of 2,141.3 seconds. This value corresponds to the summation term $\sum_{i=1}^{49} i|D_{actuali} - D_{measured}|$, representing the overall accumulated error across all successfully tracked customers.

To verify the calculation, the total sum of absolute errors is then substituted back into the original formula. This step demonstrates how the average error value, or MAE, is derived and confirms the accuracy of the computation process.

$$\text{MAE} = \frac{1}{49} \times \left(\left|D_{\text{actual}_1} - D_{\text{measured}_1}\right| + \left|D_{\text{actual}_2} - D_{\text{measured}_2}\right| + \cdots + \left|D_{\text{actual}_{49}} - D_{\text{measured}_{49}}\right|\right)$$

$$\text{MAE} = \frac{1}{49} \times (2141.3 \text{ seconds})$$

$$\text{MAE} = 43.7 \text{ seconds}$$

An MAE of 43.7 seconds indicates that, on average, the system's estimated visit durations deviate from the actual durations by 43.7 seconds, regardless of whether the estimates are longer or shorter.

5. Conclusion

This research has successfully developed and tested an intelligent system based on computer vision for analyzing customer demographics and visit duration in the coffee shop sector. The evaluation results demonstrate strong technical performance, with the system achieving 96% accuracy in gender classification, 89% accuracy in age group classification, and a Mean Absolute Error (MAE) of less than 45 seconds for dwell time estimation. These outcomes indicate that the system is both feasible and reliable for practical application. Beyond its technical achievements, the study emphasizes the importance of embedding ethical principles into system design. By applying a privacy-by-design approach, the system ensures that sensitive biometric data is not stored, and only anonymized metadata is used for analysis. This safeguards customer trust while addressing broader concerns related to data security and ethical AI adoption.

From a practical perspective, the findings suggest that such a system can provide valuable strategic insights for coffee shop operators and other SMEs. By identifying demographic patterns, visit durations, and peak customer hours, businesses can optimize staffing, marketing strategies, and spatial arrangements. These insights ultimately support better decision-making, enhance customer experience, and strengthen competitiveness in a highly saturated industry. While the study demonstrates promising results, it is not without limitations. The system was evaluated using simulated data, which, although effective for controlled testing, may not capture the full complexity of real-world environments. Future research is encouraged to apply the system in actual coffee shop settings, explore more advanced deep learning models, and expand behavioral analysis to include movement patterns or group dynamics. In conclusion, this research confirms that computer vision, when implemented with accuracy, efficiency, and ethical safeguards, can serve as a powerful tool for data-driven business strategies in the coffee shop sector.

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The data that support the findings of this study are available from the corresponding author upon reasonable request.