
IMPROVING THE ACCURACY OF REAL-TIME HUMAN COUNTING USING SURVEILLANCE CAMERAS

Research Methodology in Computer Science (AI800)



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Abstract

The proliferation of automated surveillance has made real-time human counting a critical component of modern urban management and public safety. However, existing models frequently struggle with occlusion, scale variation, and volatile lighting conditions in real-world deployments. This research proposal introduces an enhanced framework for human counting that leverages Multi-Scale Dilated Convolutional Neural Networks (MS-DCNN) integrated with a temporal consistency module. By utilizing dilated convolutions, the proposed system aims to capture features across varying scales without losing spatial resolution. Furthermore, a recurrent temporal layer is implemented to stabilize counting outputs across video frames, reducing the common issue of temporal jitter. The research methodology involves a deep-learning-based density estimation approach trained on large-scale benchmarks and optimized for real-time edge processing. The expected outcomes include a robust counting system that achieves significant error reduction in dense environments while maintaining operational efficiency.

Chapter 1: Introduction and Background

1.1 Introduction

Human counting has become a core function in modern intelligent systems. It is widely used in transportation networks, airports, shopping centers, stadiums, and public safety systems. In these environments, accurate counting is not a luxury but a requirement. Decisions such as crowd control, emergency response, and resource allocation depend on reliable real-time data.

For example, in transportation systems, passenger counting is used to adjust bus frequency and reduce congestion. In airports, monitoring crowd density helps in managing queues and improving passenger flow. In public events, counting systems play a role in preventing overcrowding and ensuring safety compliance.

Despite these practical uses, many deployed systems still fail to maintain accuracy under real-world conditions. Most existing models are developed and evaluated using benchmark datasets that contain limited variability. These datasets are often collected under controlled environments with consistent lighting, stable camera angles, and labeled data that simplifies the learning process.

In contrast, real-world environments are unpredictable. Lighting changes throughout the day, camera angles vary, and crowd behavior is dynamic. These factors introduce complexity that is not captured in standard datasets. As a result, models that perform well in testing environments often experience a significant drop in performance when deployed in real scenarios.

This gap between experimental success and practical reliability is one of the main challenges in human counting research. Improving accuracy alone is not sufficient. Systems must also be robust, stable, and capable of adapting to changing conditions. This research focuses on addressing these requirements by proposing a method that maintains consistent performance across different environments.

1.2 Background

The evolution of human counting methods reflects the broader development of computer vision. Early approaches relied on handcrafted features such as edges, motion patterns, and texture descriptors. These methods required manual tuning and were highly sensitive to environmental changes.

With the rise of deep learning, data-driven approaches replaced manual feature extraction. Neural networks can learn complex representations directly from data, leading to significant improvements in accuracy. These approaches are generally categorized into detection-based, density-based, and tracking-based methods.

Detection-based methods use object detection models to identify individuals in an image. Each detected object is counted as one person. This approach provides detailed spatial information, including bounding boxes and positions. It works well when individuals are clearly separated. However, its performance decreases in crowded scenes where people overlap. In such cases, the model may miss individuals or merge multiple people into a single detection.

Density-based methods approach the problem differently. Instead of detecting individuals, they estimate a density map over the image. Each pixel represents the likelihood of a person being present. The total count is obtained by integrating the density values. This method performs better in dense crowds because it does not rely on clear separation between individuals. However, it does not provide information about individual identities or movement.

Tracking-based methods extend detection by adding a temporal dimension. These methods follow individuals across frames in a video sequence. By assigning unique identifiers, they ensure that each person is counted once. This reduces double counting and improves consistency over time. However, tracking relies heavily on detection quality. If detection fails, tracking accuracy decreases.

Recent research has explored combining these approaches into hybrid models. The goal is to leverage the strengths of each method while reducing their weaknesses. This research builds on this idea by integrating detection with temporal consistency mechanisms to improve both accuracy and stability.

1.3 Problem Statement

Human counting systems face multiple challenges when deployed in real-world environments. These challenges directly affect accuracy and reliability, making it difficult to use such systems in critical applications.

One of the most significant challenges is occlusion. In crowded scenes, individuals often overlap or partially block each other. Detection-based models rely on visible features, so when these features are hidden, the model may fail to detect some individuals. This leads to undercounting and inconsistent results.

Lighting variation is another major issue. Real-world environments include a wide range of lighting conditions, from bright sunlight to low-light indoor settings. Shadows, reflections, and sudden changes in brightness affect the quality of input data. Since deep learning models depend on visual features, any degradation in image quality reduces detection performance.

Perspective distortion introduces additional complexity. Cameras placed at different angles capture people at different scales. Individuals closer to the camera appear larger, while those farther away appear smaller. Models trained on fixed-scale data often struggle to handle this variation, leading to uneven detection across the scene.

Another challenge is temporal instability. In video-based systems, counting results may fluctuate between frames. A person detected in one frame may be missed in the next, causing sudden changes in count values. This instability reduces trust in the system, even if the average accuracy is acceptable.

Existing methods address some of these challenges but not all of them simultaneously. Detection-based methods fail in crowded scenes, density-based methods lack temporal consistency, and tracking-based methods depend on detection quality. This creates a gap where no single method provides a complete solution.

This research addresses this gap by proposing a hybrid approach that integrates spatial detection with temporal consistency. The aim is to improve both accuracy and stability, making the system more suitable for real-world deployment.

1.4 Research Objectives

The main objective of this research is to improve the accuracy and reliability of real-time human counting systems in real-world environments.

To achieve this, the study focuses on the following objectives:

- Analyze the impact of occlusion, lighting variation, and perspective distortion on system performance
- Evaluate existing human counting methods and identify their limitations
- Design a hybrid model that combines detection and temporal consistency
- Implement the proposed model using benchmark datasets
- Evaluate performance using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)

- Improve temporal stability to reduce fluctuations between video frames

1.5 Research Scope

This research focuses on video-based human counting using surveillance cameras. The study evaluates deep learning-based approaches and proposes an improved method for real-world deployment.

The scope is limited to counting accuracy and system reliability. It does not include identity recognition, facial analysis, or behavior detection. The focus is on developing a system that provides accurate and stable counting results under varying environmental conditions.

1.6 Contribution

This research contributes to the field of computer vision by addressing practical challenges in human counting systems. The main contribution is the development of a hybrid framework that combines detection and temporal consistency mechanisms.

In addition, the study provides a structured analysis of existing methods and highlights their limitations in real-world environments. By focusing on deployment conditions rather than controlled datasets, the research aims to bridge the gap between theoretical performance and practical application.

1.7 Chapter Summary

This chapter introduced the importance of human counting in modern systems and explained the limitations of existing approaches. It discussed the evolution of counting methods and identified key challenges such as occlusion, lighting variation, and perspective distortion. The chapter also outlined the research objectives, scope, and contributions.

Chapter 2: Literature Review

2.1 Overview

This chapter reviews the major approaches used in human counting and analyzes their performance in real-world environments. The focus is not only on describing each method but also on evaluating its strengths, limitations, and suitability for practical deployment.

Human counting research has evolved from simple detection methods to more advanced deep learning techniques. These approaches can be grouped into detection-based, density-based, tracking-based, and hybrid models. Each category addresses specific challenges but also introduces new limitations.

The goal of this chapter is to identify the gap between existing solutions and real-world requirements, which forms the foundation for the proposed method.

2.2 Detection-Based Approaches

Detection-based methods aim to identify each individual in the scene using object detection models. These methods treat human counting as a standard object detection problem.

Modern detection models such as YOLO have significantly improved performance by enabling real-time processing. YOLO divides the image into grids and predicts bounding boxes along with confidence scores. This approach is efficient and suitable for real-time systems.

The main strength of detection-based methods is their ability to provide detailed spatial information. Each person is represented by a bounding box, which allows further analysis such as tracking or behavior monitoring.

However, detection-based methods face serious challenges in crowded environments. When individuals overlap, the model struggles to distinguish between them. This results in missed detections or merged bounding boxes. As crowd density increases, detection accuracy decreases significantly.

Another limitation is sensitivity to environmental conditions. Changes in lighting, shadows, or camera noise affect feature extraction and reduce detection reliability.

In summary, detection-based methods are suitable for low to medium density scenes but fail in dense and complex environments.

2.3 Density-Based Approaches

Density-based methods approach the problem differently by estimating the number of people without detecting each individual. Instead of bounding boxes, these models generate density maps where each pixel represents the likelihood of human presence.

One of the early influential models in this category is MCNN (Multi-Column Convolutional Neural Network). MCNN uses multiple convolutional columns with different receptive fields to capture features at various scales. This design allows the model to handle scale variation within the same image.

MCNN improved counting accuracy in dense scenes compared to detection-based methods. However, it requires careful tuning and does not generalize well to highly dynamic environments.

CSRNet introduced an improvement by using dilated convolution. This technique expands the receptive field without increasing the number of parameters. As a result, CSRNet captures both local and global features more effectively.

While CSRNet performs well on benchmark datasets, it still struggles with real-world conditions. It is sensitive to lighting changes and does not include temporal information.

Another model, SANet, focuses on improving feature aggregation. It combines multi-scale features to better represent complex crowd structures. This leads to improved accuracy but increases computational cost.

TEDnet further improves density estimation using multi-scale feature learning and an encoder-decoder structure. It produces high-quality density maps but lacks temporal awareness and requires significant computational resources.

The main advantage of density-based methods is their performance in dense crowds. However, they lack spatial detail and cannot track individuals. This limits their usefulness in applications that require more than just counting.

2.4 Tracking-Based Approaches

Tracking-based methods extend detection by adding temporal consistency. These methods assign unique identifiers to individuals and track them across frames.

Deep SORT is one of the most widely used tracking algorithms. It combines motion information with appearance features to match detections across frames. This allows the system to maintain identity consistency and reduce double counting.

The main strength of tracking-based methods is their ability to stabilize counting results over time. By maintaining identities, the system avoids counting the same person multiple times.

However, tracking-based methods depend heavily on detection accuracy. If detection fails in one frame, tracking becomes unreliable in subsequent frames. This creates a cascading effect where errors accumulate over time.

Tracking also introduces additional computational overhead, which may affect real-time performance in resource-constrained systems.

Overall, tracking improves temporal stability but cannot solve detection-related challenges on its own.

2.5 Real-Time Detection Models (YOLO Family)

YOLO-based models are widely used in real-time applications due to their speed and efficiency. These models process images in a single pass, making them suitable for video-based systems.

The main advantage of YOLO is its ability to achieve high frame rates while maintaining reasonable accuracy. This makes it ideal for surveillance systems where real-time processing is required.

However, YOLO models are not optimized for dense crowds. When multiple individuals overlap, the model struggles to separate them. This leads to undercounting in crowded scenes.

Another limitation is the trade-off between speed and accuracy. Increasing accuracy often reduces processing speed, which affects real-time performance.

Despite these limitations, YOLO remains a strong candidate for the detection component in hybrid systems due to its efficiency.

2.6 Transformer-Based Approaches

Transformer-based models represent a newer direction in computer vision. These models use attention mechanisms to capture relationships between different parts of the image.

The main strength of transformers is their ability to model long-range dependencies. This allows them to understand complex scenes more effectively than traditional convolutional networks.

In human counting, transformer-based models improve feature representation and handle complex crowd patterns. However, they require large amounts of data and computational resources.

This makes them less suitable for real-time applications, especially in systems with limited hardware capabilities.

In addition, transformers are still an active area of research, and their practical deployment in surveillance systems is limited.

2.7 Comparative Analysis

A comparison of the reviewed methods shows that each approach addresses specific challenges but fails to provide a complete solution.

Detection-based methods provide detailed spatial information but fail in dense scenes

Density-based methods handle crowded environments but lack tracking capability

Tracking-based methods improve temporal consistency but depend on detection accuracy

Transformer-based methods improve representation but require high computational resources

This comparison highlights that no single method is sufficient for real-world deployment.

2.8 Research Gap

The literature reveals a clear gap between research performance and real-world requirements. Most models are evaluated on controlled datasets and do not perform well under real conditions.

Key limitations identified include:

Lack of robustness to occlusion

Sensitivity to lighting variation

Inability to handle scale variation effectively

Lack of temporal stability in video-based systems

These limitations indicate the need for a hybrid approach that combines multiple techniques.

2.9 Motivation for Proposed Approach

Based on the analysis, combining detection and tracking provides a balanced solution. Detection ensures spatial accuracy, while tracking improves temporal consistency.

A hybrid approach can reduce both missed detections and double counting. It also improves stability by maintaining consistent results across frames.

This research builds on this idea by integrating detection with temporal consistency mechanisms to improve performance in real-world environments.

2.10 Chapter Summary

This chapter reviewed major approaches in human counting and analyzed their strengths and limitations. It showed that existing methods are not sufficient for real-world deployment when used independently.

The analysis identified a gap that motivates the use of hybrid approaches. The next chapter presents the proposed methodology that addresses these limitations.

Chapter 3: Research Methodology

3.1 Overview

This chapter presents the methodology used to design and evaluate the proposed human counting system. The focus is on building a robust solution that performs well in real-world environments where conditions are dynamic and unpredictable.

The proposed approach follows a hybrid architecture that combines object detection with temporal consistency mechanisms. The system is designed to improve both spatial accuracy and temporal stability, addressing the main limitations identified in previous chapters.

The methodology consists of several stages: system design, data preparation, model implementation, and performance evaluation.

3.2 System Architecture

The proposed system is built as a multi-stage pipeline that processes video input and produces real-time counting results. The system consists of three main components:

- Detection module
- Tracking module
- Counting and temporal consistency module

Each component is responsible for a specific function, and together they form an integrated solution.

The system receives a video stream as input. Each frame is processed sequentially. First, the detection module identifies individuals in the frame. Then, the tracking module assigns unique identities to each detected person. Finally, the counting module updates the total count based on tracked identities rather than raw detections.

This design ensures that each individual is counted once, even if they appear in multiple frames.

3.3 Detection Module

The detection module is responsible for identifying individuals in each frame. In this research, a real-time detection model such as YOLO is used due to its balance between speed and accuracy.

The detection process involves the following steps:

1. The input frame is resized and normalized
2. The model processes the image using convolutional layers
3. Bounding boxes are generated around detected objects
4. Confidence scores are assigned to each detection
5. Non-maximum suppression is applied to remove duplicate detections

The model is configured to detect only human objects. Threshold values are carefully selected to balance precision and recall.

Lower thresholds increase sensitivity but may introduce false positives. Higher thresholds reduce false detections but may miss individuals. Therefore, threshold tuning is critical for achieving optimal performance.

One limitation of the detection module is its sensitivity to occlusion. When individuals overlap, the model may fail to detect all people. This limitation is addressed in the tracking and temporal modules.

3.4 Tracking Module

The tracking module is used to maintain identity consistency across frames. It assigns a unique ID to each detected individual and tracks their movement over time.

In this research, a tracking algorithm such as Deep SORT is used. The tracking process involves:

- Matching detections between consecutive frames
- Using motion prediction to estimate positions
- Updating identity assignments based on similarity

The tracker uses both spatial and appearance features to maintain accuracy. When a detection is temporarily lost due to occlusion, the tracker predicts the position based on previous movement. This improves robustness in crowded scenes.

Tracking plays a key role in reducing double counting. Without tracking, the same person may be counted multiple times across frames. By maintaining identity consistency, the system ensures that each person is counted once.

However, tracking depends on detection quality. If detection fails completely, tracking may lose the target. This highlights the importance of combining both modules.

3.5 Counting and Temporal Consistency

The counting module is responsible for maintaining the total number of individuals. Instead of counting detections in each frame, the system counts unique tracked identities.

This approach reduces errors caused by repeated detections of the same individual. It also provides more stable results over time.

To further improve stability, a temporal consistency mechanism is introduced. This mechanism smooths counting results across frames to reduce fluctuations.

For example, sudden drops or spikes in count values may occur due to temporary detection failures. Temporal smoothing reduces these fluctuations and produces a more stable output.

The combination of tracking and temporal smoothing significantly improves reliability in real-time applications.

3.6 Data and Datasets

The system is evaluated using publicly available datasets that represent different crowd scenarios.

Two commonly used datasets are:

- ShanghaiTech Dataset
- UCF_CC_50 Dataset

ShanghaiTech contains a wide range of crowd densities and is divided into two parts: Part A (dense crowds) and Part B (sparser scenes). This allows evaluation under different conditions.

UCF_CC_50 contains extremely dense crowd images and is used to test model performance under challenging scenarios.

Data preprocessing includes:

- Resizing images to a fixed resolution
- Normalizing pixel values
- Applying data augmentation techniques

Augmentation techniques include brightness adjustment, noise addition, and slight geometric transformations. These techniques simulate real-world conditions and improve model robustness.

3.7 Implementation Details

The system is implemented using Python and deep learning frameworks such as PyTorch. The detection model is loaded with pretrained weights and fine-tuned if necessary.

The implementation pipeline includes:

1. Reading video input frame by frame
2. Passing each frame to the detection model
3. Applying the tracking algorithm
4. Updating the count based on tracked identities
5. Displaying results in real time

The system is designed to run efficiently to support real-time applications. Optimization techniques such as batch processing and GPU acceleration are used to improve performance.

3.8 Evaluation Metrics

The performance of the system is evaluated using standard metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)

MAE measures the average difference between predicted and actual counts. It provides a clear indication of overall accuracy.

RMSE gives more weight to larger errors, making it useful for identifying significant deviations.

In addition to these metrics, temporal stability is evaluated by analyzing fluctuations in count values across frames. A stable system should maintain consistent results over time.

3.9 Experimental Setup

The evaluation process involves testing the system on different datasets and comparing the results with existing methods.

The experimental setup includes:

- Running the detection model on test images
- Applying tracking to maintain identity consistency
- Measuring accuracy using MAE and RMSE
- Analyzing temporal stability

The results are compared with baseline methods such as detection-only and density-based approaches.

3.10 Research Milestone (Gantt Chart)

Task / Phase	Month 1	Month 2	Month 3	Month 4
Literature Review Finalization	✓			
Data Collection & Pre-processing	✓	✓		
Model Design & Implementation		✓	✓	
Model Training & Testing			✓	✓
Final Report & Documentation				✓

3.11 Chapter Summary

This chapter presented the methodology used in this research. The proposed system integrates detection, tracking, and temporal consistency to improve performance in real-world environments.

The design focuses on addressing key challenges such as occlusion, scale variation, and instability in video-based counting.

The next chapter will present the results and discuss the effectiveness of the proposed approach.

Chapter 4: Results and Discussion

4.1 Overview

This chapter presents an analytical evaluation of the proposed hybrid human counting system. Since the focus of this research is on methodology design rather than experimental deployment, the results are derived based on expected system behavior supported by findings from existing literature.

The goal of this chapter is to analyze how the proposed system performs under different conditions, compare it with existing approaches, and evaluate its strengths and limitations in real-world scenarios.

4.2 Expected Performance Behavior

The proposed hybrid model is expected to improve performance by combining spatial detection with temporal consistency. Detection ensures that individuals are accurately localized in each frame, while tracking maintains identity across frames.

In low-density environments, the system is expected to perform similarly to detection-based models, achieving high accuracy due to minimal occlusion. However, in medium and high-density environments, the advantage of the hybrid approach becomes more evident.

In crowded scenes, detection-only models often fail to identify all individuals due to overlapping objects. The integration of tracking helps compensate for these missed detections by maintaining identity information across frames. This reduces undercounting and improves overall accuracy.

Another important improvement is the reduction of counting fluctuations. In detection-only systems, the number of detected individuals may vary significantly between frames. This creates unstable outputs that reduce trust in the system. The proposed approach minimizes these fluctuations by relying on tracked identities instead of raw detections.

4.3 Quantitative Analysis

The performance of the system is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

The hybrid model is expected to achieve lower MAE compared to detection-only systems because it reduces missed detections and duplicate counting. By maintaining identity consistency, the system ensures that each individual contributes correctly to the total count.

Similarly, RMSE is expected to decrease because large errors caused by sudden detection failures are minimized. Temporal consistency helps smooth out extreme variations, resulting in more stable performance.

For example, in a scenario where a group of individuals enters a frame, a detection-only model may miss several individuals due to occlusion. This leads to a sudden drop in count followed by a correction in later frames. The hybrid model reduces this effect by tracking individuals even when detection confidence decreases.

4.4 Temporal Stability Analysis

Temporal stability is a critical factor in real-time systems. Even if the average accuracy is high, large fluctuations between frames can make the system unreliable.

The proposed approach improves temporal stability through two mechanisms:

- Identity tracking across frames
- Temporal smoothing of count values

Tracking ensures that individuals are consistently recognized, while smoothing reduces sudden spikes or drops in the count.

For instance, if a person is temporarily occluded, the tracking module can maintain their identity based on previous frames. This prevents the system from incorrectly reducing the count.

As a result, the output becomes more stable and reliable for real-time monitoring applications.

4.5 Comparative Analysis with Existing Methods

A comparison with existing approaches highlights the advantages of the proposed method.

Detection-Based Methods

Detection-only systems provide accurate results in simple scenes but fail in crowded environments. They are highly sensitive to occlusion and lighting variation. The proposed model improves upon this by adding tracking and temporal consistency.

Density-Based Methods

Density-based methods perform well in dense crowds but lack spatial detail and tracking capability. They provide a count but cannot maintain identity or support temporal analysis. The proposed approach provides both counting and identity consistency.

Tracking-Based Methods

Tracking-only approaches depend on detection input. If detection fails, tracking becomes unreliable. The hybrid model reduces this dependency by integrating both components effectively.

Overall, the proposed method provides a balanced solution that combines the strengths of all approaches.

4.6 Practical Scenario Analysis

To better understand system behavior, consider the following real-world scenarios:

Scenario 1: Crowded Public Area

In a dense crowd, individuals overlap frequently. Detection models struggle to separate individuals, leading to undercounting. The hybrid system mitigates this by tracking individuals across frames, improving accuracy.

Scenario 2: Low-Light Environment

In poor lighting conditions, detection confidence decreases. The tracking module helps maintain identity even when detection becomes uncertain, reducing performance degradation.

Scenario 3: Dynamic Movement

In environments where people move quickly, detection results may fluctuate. Tracking ensures continuity, while temporal smoothing stabilizes the count.

These scenarios demonstrate the practical advantages of the proposed system.

4.7 Limitations and Challenges

Despite its advantages, the proposed system still faces limitations.

- Severe occlusion may still cause tracking failures
- Extremely low lighting conditions reduce detection reliability
- High computational requirements may affect real-time performance on limited hardware

These limitations highlight the need for further improvements in model design and optimization.

4.8 Discussion

The results emphasize the importance of combining spatial and temporal information in human counting systems. Detection alone is not sufficient for real-world environments, and tracking alone cannot function without reliable detection.

The hybrid approach provides a practical solution by integrating both components. It improves accuracy, reduces fluctuations, and enhances reliability.

However, achieving perfect performance remains challenging. Real-world environments are complex, and no single model can handle all conditions. Continuous improvement and adaptation are required to achieve better results.

4.9 Chapter Summary

This chapter analyzed the expected performance of the proposed system and compared it with existing methods. The hybrid approach demonstrated clear advantages in terms of accuracy and stability.

The analysis showed that integrating detection and tracking provides a more reliable solution for real-time human counting. The next chapter concludes the research and outlines future directions.

Chapter 5: Conclusion and Future Work

5.1 Conclusion

This research focused on improving the accuracy of real-time human counting systems in real-world environments. The study analyzed existing approaches, identified their limitations, and proposed a hybrid model that combines detection and tracking techniques.

The analysis showed that no single method is sufficient to handle all real-world challenges. Detection-based methods struggle with occlusion, density-based methods lack tracking, and tracking methods depend on detection accuracy. The proposed hybrid approach addresses these limitations by integrating multiple techniques into a single framework.

The expected results indicate that the proposed system can improve counting accuracy, reduce errors, and provide more stable results in dynamic environments. This makes it suitable for practical deployment in surveillance systems.

5.2 Future Work

Future research can focus on improving model performance under extreme conditions such as heavy occlusion and low-light environments. Advanced models such as transformer-based architectures may be explored to improve feature representation.

Another direction is optimizing the system for edge devices to support real-time deployment with limited computational resources. This is important for practical applications where hardware constraints exist.

Additional improvements can include integrating adaptive learning mechanisms that allow the model to adjust to changing environments over time. This would improve long-term system performance.

5.3 Final Remarks

This research contributes to the field of computer vision by addressing practical challenges in human counting systems. By focusing on real-world performance, the study provides a foundation for developing more reliable and scalable solutions.

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