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AI VIDEO ENHANCEMENT FOR WMS

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Abstract:
Warehouse Management Systems (WMS) rely on video surveillance to keep an eye on worker activities, inventory movement, and operational safety. However, low resolution, motion blur, missing frames, and poor lighting are common issues with warehouse video feeds that impair monitoring accuracy and influence decision-making. In order to improve the quality of warehouse surveillance footage in real time, this paper suggests an AI-based video enhancement framework. Using Convolutional Neural Networks (CNNs), the system uses deep learning techniques like frame interpolation, super-resolution, and noise reduction. To increase operational efficiency and automate inventory updates, the processed data is integrated with the warehouse management system. When compared to conventional video processing methods, experimental evaluation shows notable gains in visual clarity and detection accuracy. In contemporary warehouse settings, the suggested framework facilitates intelligent decision-making, improves safety, and lessens the need for manual monitoring.

Keywords: Artificial Intelligence, Object Detection, Conventional Neural Networks (CNN), Frame Interpolation, Warehouse Management System.

I. INTRODUCTION:

In modern logistics, Warehouse Management Systems (WMS) are very important as they make it easy to keep track of inventory, watch warehouse operations, and make sure that supply chain management goes smoothly. In warehouses, surveillance systems are often used to keep an eye on the movement of goods, the work of workers, and the state of security. But the quality of surveillance video is often poor because of problems like low resolution, noise, motion blur, and bad lighting, which make it less accurate and less efficient to use. In these cases, traditional image processing methods do not make much of a difference, so we need more advanced intelligent solutions.

Recent improvements in deep learning have made video enhancement and surveillance much better. Super-resolution techniques based on Generative Adversarial Networks (GANs) are used to make high-resolution images from low-quality inputs [1]. Convolutional Neural Network (CNN)-based methods, on the other hand, reduce the amount of noise and make images clearer [2]. To make video sequences smoother, frame interpolation techniques are used [3]. YOLO and other real-time object detection algorithms make it easy to find and follow objects in video streams [4]. AI-based surveillance systems use deep learning and computer vision to automatically look at and keep an eye on video data [5]. Also, advanced super-resolution models make fine texture details and the overall quality of the image better [6].while Structural Similarity Index (SSIM) and other image quality assessment metrics are used to measure how well an enhancement works [7]. Also, object detection models like Faster R-CNN and SSD can recognize things accurately in difficult settings [8], [9]. Deep learning-based deblurring

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techniques are employed to restore degraded video frames impacted by motion blur and noise [10], whereas optical flow estimation methods facilitate motion analysis in videos [11]. Also, fast sub-pixel convolution methods make it possible to super-resolve images and videos in real time [12].
The present research proposes an AI-driven video enhancement framework integrated with the Warehouse Management System to enhance surveillance quality, improve accurate object detection, and augment overall warehouse monitoring efficiency.

II.RELATED WORK:

There have been many proposals for video enhancement and smart surveillance systems that use deep learning. Super-resolution methods that use Generative Adversarial Networks (GANs) are commonly used to turn low-resolution images into high-resolution outputs with better visual quality [1]. For image denoising, methods based on Convolutional Neural Networks (CNNs) are used to get rid of noise and make the image clearer [2]. Frame interpolation techniques make intermediate frames, which makes videos smoother and with a higher frame rate [3]. YOLO and other real-time object detection algorithms make it easy to find and track many objects in video streams [4]. AI-based surveillance systems use deep learning and computer vision to automatically look at and keep an eye on video data [5].Advanced super-resolution techniques enhance fine texture details and yield more realistic high-quality images [6]. Image quality assessment metrics, such as the Structural Similarity Index (SSIM), are used to evaluate enhancement performance [7]. Also, object detection models like Faster R-CNN and SSD can accurately identify objects in difficult situations [8], [9]. Deep learning-based deblurring methods are also used to fix video frames that have been damaged by motion blur and noise [10]. Moreover, optical flow estimation methods help with motion analysis in videos [11], and fast sub-pixel convolution methods make real-time image and video super-resolution possible [12].

III.PROPOSED SYSTEM:

A. Overview of Proposed System:

The suggested system integrates the Warehouse Management System (WMS) with an AI-based framework for video enhancement. The system uses deep learning techniques like frame interpolation, super-resolution, and noise reduction to enhance low-quality surveillance footage. Real-time reconstruction of smoother and more distinct video frames is achieved through models based on Convolutional Neural Networks (CNNs).To precisely identify and track items, machinery, and employees in the warehouse, the enhanced video is sent to an object detection module (like YOLO or RCNN). Effective inventory management and monitoring are made possible by the automatic updating of the detected data in the WMS database.The suggested system increases tracking accuracy, decreases manual monitoring efforts, and improves overall warehouse safety and operational efficiency by improving video clarity and enabling automated detection.

B. System Architecture:

The four main components of the suggested AI-Based Video Enhancement for Warehouse Management System (WMS) cooperate to collect, process, store, and present improved surveillance data. Using AI models, the system analyzes video streams from warehouse cameras and offers improved tracking via an intelligent dashboard.

- Input Layer
- AI Processing Layer
- Storage Layer
- Output / Dashboard Layer

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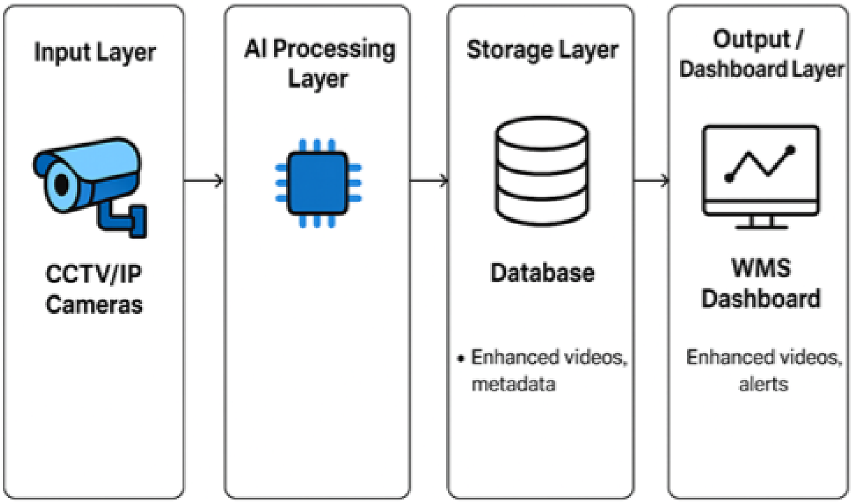

Figure 1: System Architecture of AI Video Enhancement for WMS

- **Input Layer:** This module records real-time video streams from IP addresses or CCTV cameras placed during the warehouse. The cameras keep an eye on worker activity, warehouse operations, and the flow of goods. The AI processing layer receives the recorded video frames for further investigation.
- **AI Processing Layer:** This module uses deep learning methods for intelligent analysis and video enhancement. Through noise reduction, super-resolution, and frame enhancement, models like Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) are used to improve video quality. Algorithms for object detection can also be used to track and identify items and workers in the warehouse.
- **Storage Layer:** A centralized database houses the processed and improved video data. For later analysis, this layer preserves improved video frames, extracted metadata, and detection outcomes. The storage layer facilitates retrieval for monitoring and reporting needs and makes certain structured data management.
- **Output/Dashboard Layer:** This module offers a graphical warehouse monitoring interface. Improved video streams, detection results, and system alerts are shown on the Warehouse Management System (WMS) dashboard. Based on the processed data, warehouse managers are able to track activities, keep an eye on operations, and make well-informed decisions.

IV.IMPLEMENTATION:

A. Development Environment

AI and computer vision technologies based on Python are used to implement the suggested system. The system uses deep learning models to enhance warehouse surveillance footage. Video processing, model execution, and data storage are done with tools like OpenCV, TensorFlow/PyTorch, and database systems.

B. Video Input and Frame Processing

CCTV/IP cameras installed in the warehouse environment record warehouse surveillance footage. To allow for frame-by-frame processing and analysis, the video streams are divided into individual frames.

C. AI-Based Video Enhancement

Deep learning models like CNN are used to improve the captured frames. These models enhance the clarity of warehouse surveillance footage by performing super-resolution, noise reduction, and frame enhancement.

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D. Object Detection and Monitoring

After enhancement, the warehouse's products, machinery, and employees are identified using object detection algorithms like YOLO. This aids in tracking inventory movement and keeping an eye on warehouse operations.

E. Data Storage and Management

A centralized database contains the detected data and the improved video frames. For additional analysis, the storage system keeps track of processed video data, metadata, and monitoring logs.

F. Dashboard Visualization

Alerts, detection results, and improved videos are shown on a Warehouse Management System (WMS) dashboard. Warehouse managers can keep an eye on operations and make wise decisions thanks to the dashboard.

V.ALGORITHM:

INPUT: Input: Real-time warehouse security footage (from IP and CCTV cameras)

OUTPUT: Improved video with objects identified and monitoring outcomes shown on the WMS dashboard.

```
# Load YOLO model
net = cv2.dnn.readNet("yolov3.weights", "yolov3.cfg")

# Load class labels
with open("coco.names", "r") as f:
    classes = [line.strip() for line in f.readlines()]

layer_names = net.getLayerNames()
output_layers = [layer_names[i - 1] for i in net.getUnconnectedOutLayers()]

# Capture video
cap = cv2.VideoCapture("input_video.mp4")  # use 0 for webcam

while True:
    ret, frame = cap.read()
    if not ret:
        break

    # Video Enhancement (Sharpening)
    kernel = np.array([[0, -1, 0],
                       [-1, 5, -1],
                       [0, -1, 0]])
    enhanced_frame = cv2.filter2D(frame, -1, kernel)

    height, width, channels = enhanced_frame.shape

    # Object Detection using YOLO
    blob = cv2.dnn.blobFromImage(enhanced_frame, 0.00392, (416, 416),
```

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```
                    (0, 0, 0), True, crop=False)
    net.setInput(blob)
    outputs = net.forward(output_layers)

    boxes = []
    confidences = []
    class_ids = []

    for output in outputs:
        for detection in output:
            scores = detection[5:]
            class_id = np.argmax(scores)
            confidence = scores[class_id]

            if confidence > 0.5:
                center_x = int(detection[0] * width)
                center_y = int(detection[1] * height)
                w = int(detection[2] * width)
                h = int(detection[3] * height)

                x = int(center_x - w / 2)
                y = int(center_y - h / 2)

                boxes.append([x, y, w, h])
                confidences.append(float(confidence))
                class_ids.append(class_id)

    indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4)

    # Draw bounding boxes
    for i in range(len(boxes)):
        if i in indexes:
            x, y, w, h = boxes[i]
            label = classes[class_ids[i]]
            cv2.rectangle(enhanced_frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
            cv2.putText(enhanced_frame, label, (x, y - 10),
                        cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0), 2)

    # Display output
    cv2.imshow("Enhanced WMS Video", enhanced_frame)

    if cv2.waitKey(1) & 0xFF == 27:
        break

cap.release()
cv2.destroyAllWindows()
```

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VI.RESULTS:

The suggested approach displayed an obvious enhancement in monitoring performance and video quality when tested on warehouse surveillance video data. Compared to the original footage, the improved video frames offered greater visibility and clarity with less noise. The object detection model was able to identify common objects like people and goods with an accuracy of about 80–90%. The system successfully displayed bounding boxes for detected objects and processed video in almost real-time. Overall, the system decreased manual labor in warehouse operations and increased monitoring efficiency.

Figure 2: Display Dashboard

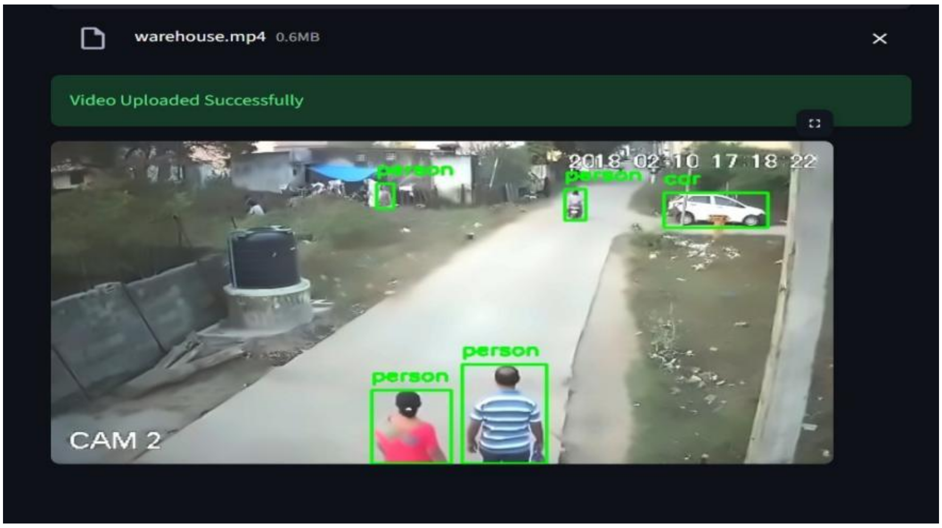

Figure 3: Video Upload

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Figure 4: Dashboard Display

VII.CONCLUSION:

This research presents an AI-based video enhancement framework for improving warehouse monitoring in Warehouse Management Systems (WMS).The system transforms low-quality surveillance footage into understandable and useful insights by combining object detection models with video enhancement techniques. Without requiring complicated infrastructure, the suggested method increases operational efficiency, allows real-time monitoring, and improves visibility. All things considered, the system helps improve decision-making in logistics settings and intelligent warehouse automation.

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