SMART CCTV ATTENDANCE SYSTEM WITH TAILGATING DETECTION

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AUTHOR’S DECLARATION

ChatGPT (Deep Research Mode) was used to search, verify, and summarize research papers and to generate the narrative literature review. All links were opened and confirmed by the team. All reviewed papers were added to the GitHub repository under /docs/references.

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1. INTRODUCTION

In the modern world of heightened security awareness, trusted access and attendance monitoring are inevitable. Conventional manual systems or card-based systems are ineffective and prone to malfunction, proxy attendance and tailgating attacks. The proposed Smart CCTV Attendance System with Tailgating Detection is aimed at solving these issues by integrating face recognition-based attendance tracking with smart surveillance to prevent tailgating in real-time. With the help of advanced computer vision software and deep learning algorithms, the proposed system will be capable of automatically detecting, identifying and tracking individuals and at the same time scanning entry points for attempts of unauthorized access. In order to meet real-time performance and scalability requirements, the implementation of the system will be done on a resource-constrained edge device platform like the NVIDIA Jetson Nano 4GB development kit. Together, forming a privacy-conscious and efficient AI-based solution that can be applied in modern institutions and organizations.

2. LITERATURE REVIEW

Recent studies have proven that face recognition developed by deep learning algorithms is useful for marking attendance automatically. To prevent proxy attendance with adjustable presence thresholds, Rao [1] suggested AttenFace, which is a real-time attendance system that captures classroom snapshots within an interval of every 10 minutes and allows parallel face recognition between active classes. The modular design isolates face recognition servers and back-end attendance computation to provide easy interoperability with the learning management system, along with a great reduction in computation compared to continuous video processing. To complement this solution, O. Faruque et al. [2] provided an in-depth comparative research of detection models (HaarCascade, SSD, MTCNN, YOLOv5) and recognition models (LBPH, FaceNet, ArcFace, DeepFace), revealing that the combination of YOLOv5 and ArcFace is effective at multi-face detection in single images, which makes it especially appropriate in mass attendance cases in educational and organizational contexts.

Controlling the issue of security gap in tailgating, Siegmund et al. [3] introduced a new method that involved the combination of capacitive floor sensors and overhead camera-based CNN classification, accessing GoogLeNet architecture in accordance with which the detection percentage of piggybacking was 92.9 percent as a result of multi-sensor fusion. The motion extraction and the CNN classification image-based illustration show the efficiency of computation that can be applied in an embedded system. Most recently, Ahamed et al. [4] further refined the equipment with an overhead people tracking system specifically designed to handle doorway-based scenarios and featured a combination of finetuned SSD MobileNet secure object detection and a custom feature-based tracker alongside a three-region field of view count algorithm already capable of running at 20-27 FPS on small-scale edge computers. Such a strategy is robust to occlusions and environmental changes that are important in a deployed application. Moreover, at CVPR 2019, Lian et al. [5] proposed the Regression Guided Detection Network (RDNet), which applies depth-adaptive kernels and density maps at the same time to count and localize head in crowded scenes, and the geometric approach is directly applicable to tailgating scenarios using a single camera.

Effective implementation on edge devices with constrained resources requires optimizing both memory and computational efficiency. Jeong et al. [6] proposed a complete heterogeneous processor-based Framework with 101 percent to 680 percent performance with heterogeneous processor usage, multi-threading, pipelining, and optimization of layer placement, and with up to 55 percent energy savings over nine real-life benchmarks using TensorRT. There are optimization strategies that have the necessary implementation guidelines to implement face recognition models on Jetson Nano hardware. Sarvajcz et al. [7] have shown the practical real-time computer vision of dual-camera NVIDIA Jetson Nano B01 platform with the SSD-MobileNet-v1, including a conversion of the TensorRT framework (TensorFlow to ONNX), performance optimization (FP32/FP16/INT8) and layer fusion, and reported real-time inference at the power consumption of 5-10W. The following implementation plan applies directly to the JetBot hardware appliances in the case of attendance systems. Duong et al. [8] extensively cover survey-wise deep learning-based anomaly detection in video surveillance, splitting the approaches into supervised, semi-supervised, unsupervised, and weakly-supervised methods and addressing preprocessing methods, benchmark databases, and challenges such as occlusions and dynamic scenes.

Efficient Frameworks of the model are imperative to edge deployment. Xu et al. [9] proposed CenterFace, an Anchor-free single-stage face detector, with keypoint-based face coding, with WIDER FACE benchmark results of 0.935/0.924/0.875 (Easy/Medium/Hard) representing the state of the art and keypoint face representation, such that 200 FPS is achievable on high-end GPUs, and single CPU cores can run it at real-time. Its marketability can be attributed to the design of the lightweight anchor-free device that allows it to be used to deploy Jetson Nano. Recently, George et al. [10] introduced EdgeFace, a novel and modern hybrid CNN-Transformer model with just 1.77M parameters that attains 99.73 percent accuracy on LFW at the cost of computational efficiency via Low Rank Linear modules and Split Depth-wise Transpose Attention encoders as the winner model of the IJCB 2023 Efficient Face Recognition Competition. These developments follow the classical FaceNet architecture, introduced by Schroff et al. [11], which transformed faces recognition with Triplet loss and online mining to learn directly the embeddings in Euclidean spaces with the strength of such space that the distance between faces is proportional to their similarity, with its 99.63 percent accuracy on LFW with only 128 bytes per face. Keerthana et al. [12] came up with a Tailgating Detection and Security Alerting System that used the YOLOv3 object detection model using OpenCV to detect unauthorized access when it is in restricted zones. The system identifies door boundaries and tallies the number of people entering the household each time it is authenticated, raising an alert when multiple persons enter. The strategy shows deep learning deployed effectively in a real-time access monitor and provides a foundation toward the improvement of security with embedded and edge-based AI systems.

Reviewed literature has shown that tailgating-detecting smart CCTV attendance system is technically achievable on a NVIDIA Jetson Nano 4GB platform. This is due to the fact that lightweight face detection architectures (CenterFace [9]) combined with efficient recognition architectures (EdgeFace [10] or default versions of MobileFaceNet) and Tensor RT optimization frameworks [6][7] offer an easy path of implementation. Multi-person tracking systems [4][5][12], provide proven techniques to identify unauthorized intrusion, and deployed attendance systems based in the real world [1][2] are established to be practical during the implementation in educational environments.

Although intelligent surveillance and automated attendance are rapidly becoming popular, most current solutions view face recognition and tailgating detection as two distinct issues, frequently powered by high-performance cloud-based infrastructure or solution packages that are not cost-effective or privacy-sensitive in deployable location. This leaves a distinct gap within research to include the development of an integrated and light weighted solution capable of executing real-time face recognition to check attendance and identify tailgating actions through a single edge device while maintaining the system stability. Even though the reviewed studies demonstrate significant advancements in accuracy and efficiency, they are mostly confined to controlled conditions and isolated functionalities. Practical considerations, like variability of the real-life environment, scalability in real-time, and sustainability, are not often discussed. Such matters highlight that a hybrid, resource-efficient architecture with optimized performance on limited edge platforms such as NVIDIA Jetson Nano is required.

3. PROJECT FEASIBILITY ANALYSIS

Based on the reviewed literature and identified limitations, the following part outlines the proposed research direction and evaluates the feasibility of implementing such an integrated system under real-world operational constraints.

This project will address that gap by constructing a two-phase system on the NVIDIA Jetson Nano 4GB Dev Kit. The first stage will be spent on proper attendance tracking, facial recognition (YOLOv5) [2] and recognition (ArcFace [2] or its lightweight analogue) algorithms, the second stage will be devoted to the implementation of the tailing-gating detection system in real-time [12], working with the number of people passing through a regulated entrance. We focus on limited hardware optimization, real-time tasks, and workability, which are commonly used in school or office life. The following feasibility assessment explores the system’s technical suitability, mode choices, Jetson Nano capabilities, team structure and development timeline.

Through the methods outlined in Papers [1], [2], and [12], this project will be used to deploy a feasible, practical undertaking model of a Smart CCTV Attendance System containing Tailgating Detection.

The proposed system's flow diagram below depicts the stages of the implementation plan and hardware system of the proposed system.

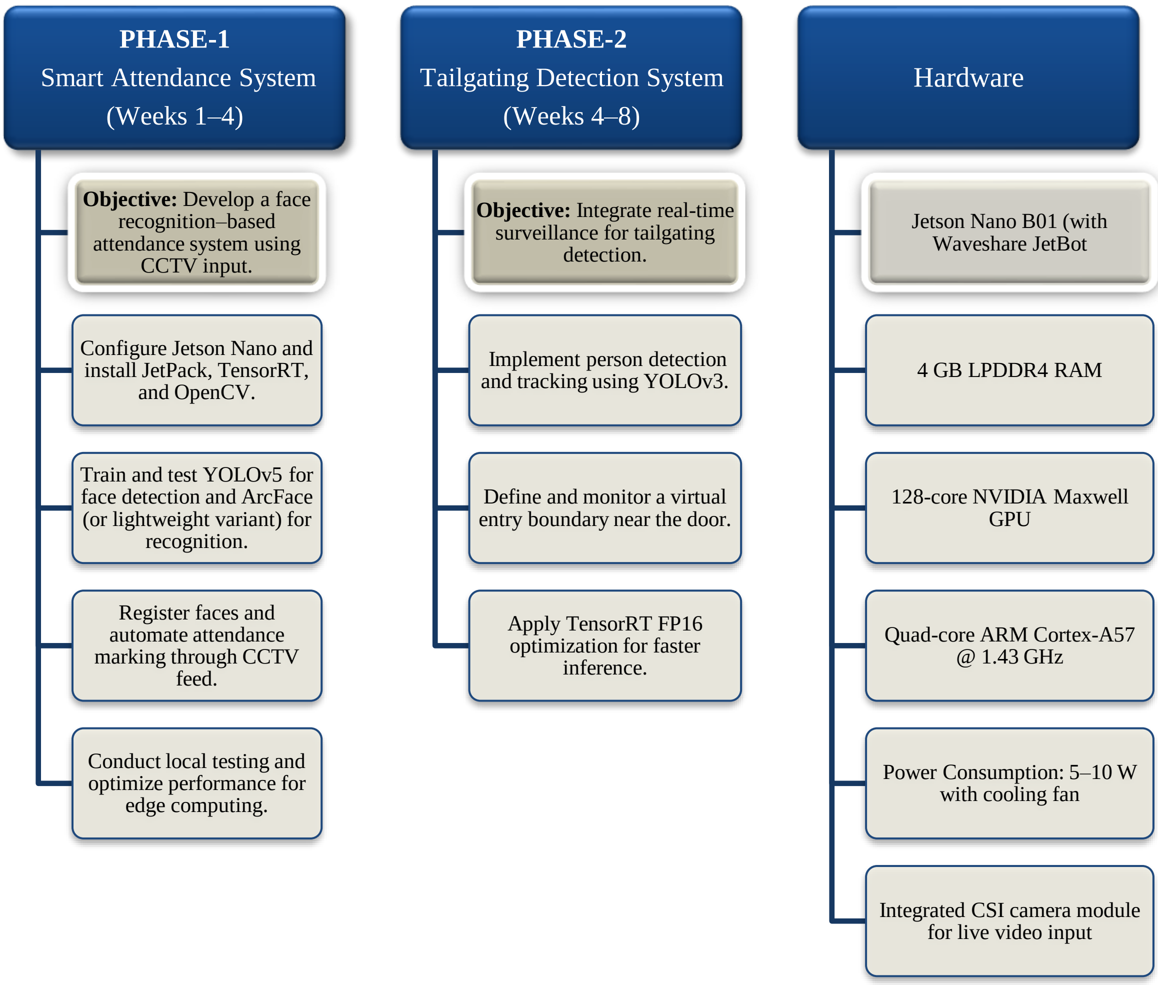

Figure 1: Flow Diagram for the Proposed System's Feasibility

The expected outcome of the project is illustrated as follows

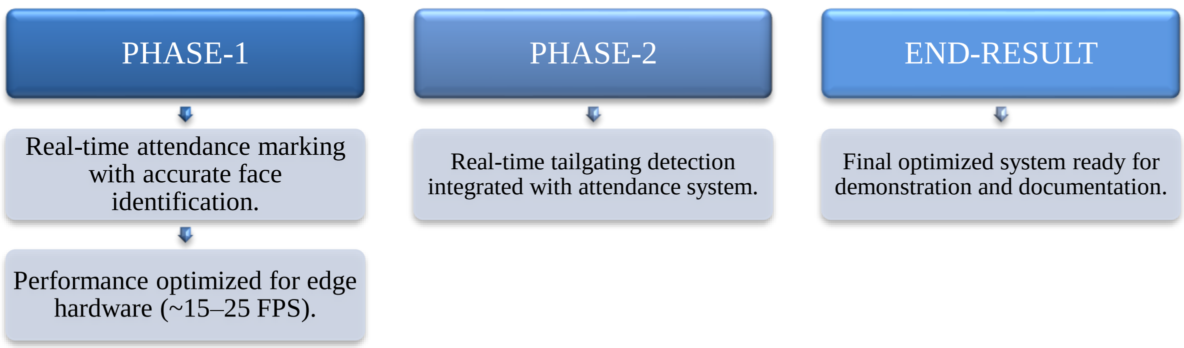

Figure 2: Expected Outcome for the Proposed System

Table 1.1: Roles of Team Members

S. No.	**Members**	**Roles**	**Responsibilities**
1	Umbreen Shah Nawaz	Documentation Life Cycle	• Manage Project Schedule and GitHub updates • Preparation of reports and presentations • Maintain Documentation and ensure overall coordination
2	Muhammad Ali Tahir	Simulation and Algorithm	• Develop face recognition and tailgating detection algorithms. • Train and Test Models • Optimize and integrate for real-time processing
3	Hamza Khan	Embedded System	• Deploy optimized models on NVIDIA Jetson Nano • Configure Hardware, camera, and performance tests • Ensure efficient on-device processing

4. GITHUB REPOSITORY

A shared GitHub repository will be used as a means to store all the project elements such as code, documentation, datasets, and analysis output to support successful collaboration, as well as development management. The repository has a well-organized structure to navigate easily and enables instructors and team members to track the growth and progress freely.

The repository can be accessed at:

https://github.com/alit2204/smart-cctv-attendance-jetson

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