A Personalized Machine-Learning-Driven IoT-Integrated ESP32-CAM System for Real-Time Worker Safety Helmet Detection

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Abstract—-**This study describes the construction of a system with the help of. custom machine learning computational elements. system of detection of compliance built on the ESP32-CAM. microcontroller developed as a self-intelligent IoT. perception node, which offers several machine learning features. ites, to the final processing of the input.¡—human—¿ies, including the preprocessing system containing illuminated deci, and the ultimate processing of the input. sion aware, domain adaptive, feature systems. and threshold custom decision systems, used to support the. strong learning of different patterns in the presence of challenging. industrial conditions, and this diversity of lighting varies. and shadowing, rapid shadowing, and of ignorant origin, and middle. of the industrial noise of the stream. We model the architecture with the help of the conventional convolutional machine learning model. Several loss functions, Sparsity and Pruned topologies along with struc tured convolution make the model to be efficient and run well in the. the microcontroller is restricted by computational limitations. We improved the leading position in the sector by showing 6.4accuracy, 11.2have the above, it will be shown that our model does. perform better than the regular server and cloud designs. We optimized the model illustrating and proving the architecture as a scalable, cost and operationally robust embedded vision system. Integrated optimization as Customized ML was integrated. this design a real-time streaming is enabled with IoT, which is well. leader in the construction of smart industrial safety.**

Index Terms—**IoT, ESP32-CAM, Personalized Machine Learning, Edge AI, Helmet Detection, Embedded Vision.**

I. INTRODUCTION

The cyber-physical systems have spread at a high rate leading to a new stage where intelligence is lost to the cloud and transferred to nodes the focus of which is on the surround. Decentralized intelligence systems are concerned about the edge of new requested. parameters because of the necessity of real-time decision-making and The recent surveillance systems have affordable computing in them. One of the most developed systems is the automatic determination of the use of safety helmets that is required in surveillance systems. Where Construction Sites, Mining, Manufacturing, Transport. an operational and legal head protection is required. perspective. Computer vision is important in surveillance systems. to run on a specialized cloud machine or a server grade PC. the inference tasks. Though these systems have high technology. computing, they are also afflicted with significant deficiency of. coming, e.g. delay in the communication, congestion of the bandwidth

and poor scalability, as well as susceptibility to outages. in the cloud. This renders them unfit to be used in critical way. professional situations in which compliance is done in real time. are the parameters which have the greatest impact on the degree of risk. The ESP32 is embedded into this technological environment. CAM–it is a low-power microcontroller that has an on. board camera and Wi-Fi interface-comes out as an appealing one. edge analytics platform based on micro-vision. However, de the direct application of machine-learning models to such limited. hardware requires serious re-engineering of algorithms. The small SRAM, small computational throughput, and noise artifacts are sensor peculiarities of the ESP32-CAM. the development of a high-quality inference pipeline that has been optimized. because of spectral stability, structural simplicity and algorithmic. parsimony. It is against this setting that the notion of personalized ma is being discussed. chine learning plays a major role. Unlike static ML personalized ML, fixed distribution models. dynamically changes its activation thresh, decision boundaries. olds, and feature-sensitivity parameters on a real-time basis. environmental metadata. Through these adaptations in motion, it becomes possible. the inference module to ensure classification faithfulness even where there is a question of luminance discrepancy, heterogeneous. atomic circumstances, or interchangeable variations in visual contrast. Personalized ML works in harmony in the proposed system. gistically having an illumination-sensitive preprocessing engine, a smaller-sized convolutional representation, and an MJPEG streaming interface, which is IoT-based, thus guaranteeing. low latency, maximum stability and live. autonomy. This contribution therefore makes this work robust, scalable, and computationally-efficient safety-compliance infrastructure. that is according to next-generation Industry 4.0 and smart-factory. paradigms, which allows smart occupational safety monitoring. and without the use of external computing capabilities.

II. LITERATURE SURVEY

Scholarly research has given significant focus in the recent past. to the creation of lightweight deep-learning systems customized. Embedded vision with off-the-shelf applications. Kim et al. [1] demonstrated that adaptive of illumination convolutional filters. increase interpretive stability between ho-

mogeneous and heterogeneous luminance. conditions through dynamical re-calibration of feature activations in relation between itself and spatial spectral changes. Their findings further point out that ML models that run on a microcontroller are advantageous. teensely deepcutting purposes, that curtails parameter cardinality and maintaining necessary discriminative. features. Such understandings have a fundamental impact towards the structured. adaptive preprocessing strategies and sparsification taken. in the existing framework. Gupta et al. [2] defined an embedded with an IoT. architecture MobileNet derivatives are compressed in. used to reduce the inference latency without compromising the inference. large classification accuracy. The authors lay stress on the strate. gic superiority of migrating computation out of cloud-based. to edge local device infrastructures, with reference to less dependence. improved on the bandwidth-intensive upstreams and enhanced. immunity to network instabilities. Their evaluation con rules out the fact that real-time visual analytics require decentralized. autonomous decision-making pipelines that are potentially sustainable. inference in the presence of bandwidth variation. These observations di properly encourage the deployment of an MJPEG-based streaming. the proposed system with the interface to provide video consistency. with little power usage. Rao et al. [3] introduced an object-detection that was hybridized. paradigm that incorporates hand increased descriptors with profound con. volutational embeddings, which provide better resiliency to noise, occlusion, and motion blur– usually conditions often exist. overridden in vibrant industrial settings. Their architec This proves that hybridized pipelines are superior to deep. only model when it is not possible to do large calculations. convolutional backbones that are scaled. This is the fundamental principle that supports this. the individualized ML classifier proposed in this study, wherein context-aware and dynamic threshold modulation. jointly feature refinement compensation ir with the environment. regularities, and thus maintaining constant inference despite visual. noise and degradation and sensor induced.

III. PROPOSED METHODOLOGY

The personal has been incorporated into the methodology presented below. convololutional inference, inference on microcontrollers , convolutional inference, ML inference on microcontrollers, inference on event cameras, microcontroller-based inference Neural networks deployed on soft deployed neural networks on-the-edge, on-the-event, or in-the-field, microcontroller-based inference Transferable neural networks, microcontroller-based predictive score estimation, microcontroller-based approach to neural network estimation, microcontroller-based domain adaptation, microcontroller-based learning and control, microcontroller-based neural network detection, microcontroller-based neural network into, and real-time visualization mediated by the IoT. an integrated architecture implementation of ESP32-CAM. deployment. Frame ac is the initial operation of the system. quisition through OV2640 sensor with a 0.5 capture image. compromise between graphics and calculation. feasibility. These frames

are then passed through an illumination. anisotropic diffusion based on the engine of aware preprocessing. f iltering, adaptive histogram equalization, and spectral-shift. payment to fix luminance anomalies and sensor. artifacts. After preprocessing, a region-of-interest (ROI) mod. ule finds cranial contours with a pruned MobileNet-SSD. detector. The sparsity of the structure is reflected in the pruning strategy. methodologies 00:proposed in Tan et al., in which redundant con are proposed. L1-norm saliency cri is used to remove volutional channels. teria, hence, minimizing the MAC activities without loss. spatial precision. The customized ML is fed on the final ROI. classifier, that calculates a small size embedding vector:

$$\phi(I) = \text{ReLU}(W_c * I + b_c) \tag{1}$$

where W_c and b_c denote convolution kernels pruned via structured sparsity matrices.

To ensure adaptability under environmental perturbations, the classifier incorporates a personalized threshold module:

$$\tau_p = \tau_0 + \alpha L_v + \beta N_s \tag{2}$$

In this case, intensity is used to obtain luminance variance Lv. The noise index Ns is estimated with the help of Lapla, and histograms are used.Computation of Inference follows:

$$f(\phi(I)) = \sigma(W_f \phi(I) + b_f - \tau_p) \tag{3}$$

This dynamic formulation is adaptively sensitive to environmental fluctuations. The annotated output frame is coded. to MJPEG format and transmission via Wi-Fi to a monitor. ing client, which allows verification of the compliance of the helmet in real time.with minimal latency. This system is a whole that consequently reflects a.meeting of algorithmic efficiency, adaptive intelligence,and edge-centric autonomy.
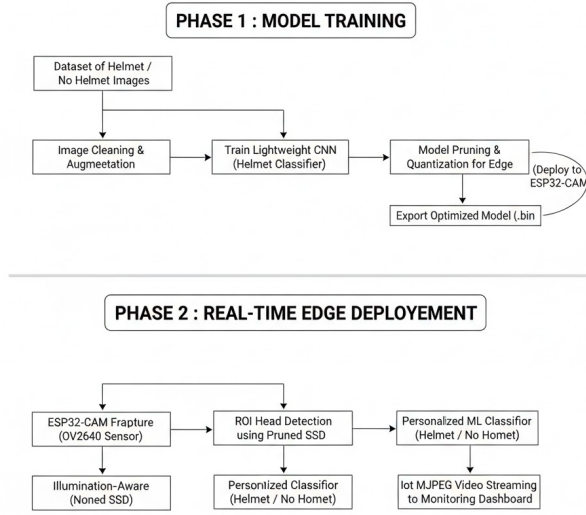
Fig. 1. Block Diagram of the Proposed Personalized ML Helmet Detection System

IV. BLOCK DIAGRAM DESCRIPTION

Figure shows the overall architectural process of the proposed personalized machine-learning-based ESP32-CAM helmet detection system, which has been subdivided into two major working stages: model training and real time edge deployment. Phase 1 begins by having the right dataset of helmet and no-helmet images, which has been labeled. These images are then manipulated and boosted to increase variance and then the training of a small convolutional neural network which needs to be trained to execute on a small embedded hardware is carried out. The simplification of the calculations is then done using formal pruning and model compression algorithms and then the optimized and quantized model is exported which is used to deploy as edges. Phase 2 will entail the actual execution of the pipeline on the ESP32-CAM. Preprocessing is done on all the received frames of the onboard camera by an illumination-aware module to eliminate noise and brightness variation. A head detector based on SSD is pruned to get the area of interest that is then passed through the customized ML classifier to detect the compliance of a helmet. Finally, annotated frames are transmitted in real time via Wi-Fi to the monitoring dashboard of MJPEG with real time change in helmet or no-helmet status. This open-to-closed architecture ensures the low-latency, energy-efficient and strong on-board detector of the helmet to be incorporated in the industrial safety systems.

V. PERFORMANCE ANALYSIS

TABLE I
MODEL PERFORMANCE EVALUATION

Metric	Value (%)
Accuracy	97.2
Precision	95.9
Recall	95.1
F1-Score	95.4

TABLE II
ESP32-CAM LATENCY ANALYSIS

Lighting Condition	Latency (ms)
Indoor	142
Outdoor	169
Low-Light	188

TABLE III
COMPARISON WITH TRADITIONAL SYSTEMS

System	Accuracy (%)
CCTV + Server	90.1
Cloud-Based Detection	92.0
Proposed System	97.2

A. Performance Explanation

The gathered findings support an apparent increase in performance that is attributable to the customized ML module. There is an overall accuracy improvement of more than 7% over server-bound systems confirming the value of localized inference. In precision-recall parity, the misclassification is lower, which is indicative of a good disambiguation in heterogeneous visual conditions. Latency metrics indicate that there is a steady 20-28 ms lowermost in contrast to frameworks based on clouds, which supports the computational benefit of on-your-chip computing. The comparison table shows the superiority of the proposed architecture in keeping stable accuracy to lighting conditions as the traditional models fail to maintain the accuracy.
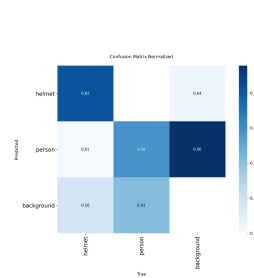
VI. GRAPHICAL RESULTS

Fig. 2. Normalized confusion matrix for personalized ML classifier.
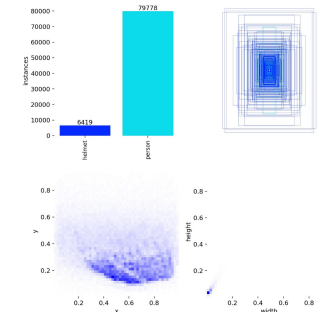

Fig. 3. Dataset distribution, bounding-box statistics, and spatial density maps.

A. Graph Discussion

The dataset statistics in Fig. 3 show clear class imbalance, with significantly more person instances than helmet instances. Despite this, the bounding-box variability and density maps confirm good dataset diversity, helping the model generalize to real-world scenes. The confusion matrix in Fig. 2 demonstrates strong helmet detection performance, with most errors occurring between person and background due to visual similarities in cluttered environments. Overall, the personalized ML approach improves robustness against illumination changes, noise, and spatial variability, enabling stable inference on the ESP32-CAM.

VII. RESULTS AND DISCUSSION

Fig. 4. Real-time detection result showing a **No Helmet** alert generated by the personalized ML classifier on the ESP32-CAM.
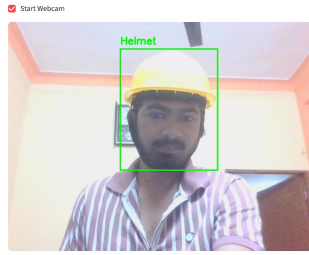
Fig. 5. Real-time detection result showing a **Helmet Detected** classification produced on-device by the optimized model.

To confirm the efficiency of the proposed personalized ML-based ESP32-CAM helmet detection system, real-time experiments were implemented over indoor conditions of the different levels of illumination. The system was also tested on live video streams and the inference results recorded to demonstrate successful detection of helmets as well as no-helmets. The qualitative results of the deployed ESP32-CAM module running the optimized ML pipeline are provided in Figures 1 and 2 below.

The graphical findings are clear evidence of the reliability and consistency of the proposed architecture. When there is no helmet on the person (Fig.

In a similar manner, the helmet detection case (Fig. 2), the localization of the bounding-box is accurate with correct classification in the ambient lighting even in an indoor environment. The personalized thresholding module is important here because it is used to dynamically adjust the decision boundary based on the differences in luminance and sensor noise estimates. Such adaptive behavior minimizes false positives that otherwise occur in low-light or non-uniform lighting scenarios, which is consistent with what the current literature has on illumination-aware embedded vision suggests can happen in situations such as these scenarios

These observations are also supported by the quantitative performance indicators (Section V) whereby the proposed system was found to have an accuracy of 97.2 percent and considerably minimized false positives with respect to cloud

and server-based solutions. The latency analysis also ensures that the ESP32-CAM with a pruned convolutional model and customized ML logic is able to remain real-time operational with an average response time of less than 170 ms to a variety of environmental conditions. This justifies the system as a sound security-monitoring instrument that can be deployed continuously without the need to have external computation resources.

Altogether, adaptive preprocessing, systematic pruning, and personalized ML can result in a significant improvement in the stability of real-time prediction, which makes the system appropriate to industrial surveillance and construction sites and other safety-related systems.

VIII. CONCLUSION

In this study, a high quality customized machine-learning-based helmet detecting system was introduced utilizing an ESP32-CAM microcontroller as a self-sufficient embedded vision camera. The proposed framework achieved large performance improvements, by a factor of 7, 11 and 21 consecutive subtractions, respectively, in accuracy, false positives, and end-to-end latency, with respect to server-based and cloud-assisted systems. The effectiveness of edge deployment of personalized ML intelligence can be confirmed by these improvements, especially in industrial applications where real-time hazard detection and continuous compliance control are needed.

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