Kasu Journal of Computer Science Vol.3 No.2 [June, 2026], pp. 100-131
https://doi.org//10.47514/kjcs/2026.3.2.003

Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

An Edge-Cloud Deep Learning Architecture for Secure Attendance Monitoring in Resource-Constrained Educational Environments

Adewole David Bamidele[1]

[1]Department of Software Engineering, Federal University of Technology, Akure, Nigeria

dbadewole@futa.edu.ng[1]

Abstract

Existing attendance monitoring mechanisms in schools are facing several challenges especially in resource-constrained educational settings. The menace of truancy, absenteeism, proxy attendance and unfettered access to school premises by unauthorized persons pose serious security concerns at a time of spike in global terrorism and banditry activities. These challenges require technology-based proactive solutions to guarantee administrative responsibility and student safety. In this paper, a novel architecture of edge cloud deep learning is proposed which is tailored to address the problem of attendance tracking in real time in Nigerian educational sector. This system leverages Convolutional Neural Network (CNN) for biometric face recognition at the edge of the network, using a React web interface powered by TensorFlow.js. In place of the extremely hefty computational and bandwidth restrictions of the traditional centralized systems, a lightweight NoSQL cloud-based infrastructure (Firebase) is used for state management and real-time synchronization. Empirical evaluations were performed under dynamic real-world conditions with different light and physical occlusion. The model achieved a validation accuracy of 96.72% while on the edge, it had an inference latency of 185ms per frame and a cloud synchronization latency of 112ms per transaction. The system is essentially a transformation of how a basic administrative task is conducted into an active safeguarding tool which safeguards the wellbeing of students in traditionally very important and dynamic academic environments.

Keywords: Convolutional Neural Networks, Data Privacy, Edge-Cloud Architecture, Facial Recognition, Resource-Constrained Environments, Smart Education Systems.

1. Introduction

It is an essential practice and duty of educational institutions to monitor student attendance. It is not only a key indicator of academic involvement and practice, but is also a pivotal indicator for institutional accountability and student safety (Syahidi et al., 2025; Aposika, 2026). However, in Nigeria and other developing countries, education institutions are still faced with the institutional shortcomings of the conventional attendance systems. A paper-based sign-in system and the roll call system are prone to human factors, administrative negligence and malicious alteration (Ogunje et al., 2024; Orjiakor et al., 2025). Worse yet, the high cases of proxy attendance and impersonation as well as very serious security threats of the contemporary times such as unauthorized intrusions into the campus, targeted kidnapping of students from several parts of the country makes it clear that there is a deep seated need of security management systems that are robust and cannot be easily tampered with (Oshita et al., 2019). In the past, institutions have tried to overcome these operational problems by implementing early-generation automation technologies, such as Radio Frequency Identification (RFID) and standalone fingerprints scanners (Ohanu et al., 2023). Worse still, the high incidences of proxy attendance and impersonation are now compounded by severe contemporary security threats, highlighting an urgent, deep-seated need for robust, tamper-proof security management systems (Oshita et al., 2019). Recent empirical case studies have documented how the prolonged threat of collective violence, including armed kidnapping and harassment, severely restricts academic engagement and student well-being in Northern Nigeria (Shockden et al., 2023). Furthermore, localized studies in South-West Nigeria, specifically within Ondo State, Nigeria confirm that youths and students are increasingly exposed to severe security threats, notably occasional kidnapping for ransom and physical exploitation. These compounding regional security breaches fundamentally compromise the safety of modern educational campuses, rendering standalone legacy systems ill-equipped to alert administrators to active physical threats in a timely manner (Adewumi & Bwowe, 2024). But these legacy technologies exhibits some key challenges when used in resource-limited environments. These challenges include prohibitive deployment costs, lack of a broadband campus-wide Internet connectivity and high susceptibility to physical tampering and spoofing (Imran et al., 2024). In addition, standalone and offline systems are simply under-equipped to effectively respond to the changing security requirements of a contemporary school campus, without the ability of real-time, centralized monitoring and alerting system to provide immediate warning to administrators of a potential physical threat (Ali et al., 2024). The introduction of Artificial Intelligence (AI), especially, computer vision and deep learning, has been a game-changer in non-intrusive identity verification, presenting a solution to eliminate the “inescapable” weaknesses of manual administrative processes (Sultana, 2025). In particular, CNN has proven to be remarkably good at facial recognition, because they can learn the complex spatial structure of image data on their own (LeCun et al., 2015; Kasar et al., 2016; Suresh et al., 2019). However, there exist large research gaps, particularly the application of the most cutting edge deep learning models in developing regions, where architectural and infrastructural challenges are significant. Deep neural networks use lots of computations. Centralized cloud inference brings prohibitive network latency and system failures to academic environments in Sub-Saharan countries where power is often in short supply, internet connectivity is unreliable, and high-end, local Graphical Processing Units (GPUs) are unavailable. On the other hand, the power limits of traditional institutional hardware limits the use of common high-end edge deployments(Winarno et al., 2019; Andrejevic and Selwyn, 2020; Teoh et al., 2021). To overcome this computational dichotomy, this paper provides a novel Edge-Cloud computing architecture. This approach is different from distributing high-resolution video streams to a central server where the inference algorithms are processed, but instead performing the computation at the network edge. The CNN runs natively on the client-side browser, thanks to TensorFlow.js being integrated into the web app using React. At the same time, the system uses a light-weight NoSQL cloud database for real time management of the system states and attendance logs. The hybrid approach successfully removes the need for heavy computation on the server side, guarantees low latency localized inference and ensures that administrative stakeholders can have centralized and real-time control. The aim of this research is to design, implement and critically assess an AI based attendance management system that uses facial recognition technology to enhance the accountability of educational institutions and eliminate insecurity in school premises in Nigeria. The specific objectives are to:

a. design and train a lightweight CNN for high accuracy of face recognition under dynamic environments in real world.
b. eliminate dependency on bandwidth and hardware limitations using an Edge-Cloud partitioning framework with TensorFlow.js and Firebase.
c. assess the architecture's system-wide operational performance, including edge inference latency, cloud synchronization delay and the ability of the model to maintain performance when subjected to physical occlusion and ambient light changes.

2. Related Works

Ogunje et al. (2024) was motivated by the inefficiencies of manual attendance tracking in Nigerian tertiary institutions, such as time loss, impersonation, and poor student performance, the work employs a literature review methodology to synthesize automated tracking mechanisms like biometrics, RFID, and mobile applications. The study contributes to knowledge by highlighting the specific advantages of these automated systems, particularly their capacity to significantly enhance data accuracy, time efficiency, and administrative compliance. However, a notable limitation is the study's reliance on secondary literature without providing primary empirical data. Consequently, the authors strongly advocate for increased funding and future localized research to properly develop and implement these automated technologies across Nigerian educational institutions. Dalhatu et al. (2025) applies the use of technology to track castle rustling which is a serious economic and security concern in Northen

Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

Nigeria. The research was motivated by the socio-economic danger posed by the cattle rustling in Nigeria and this study aims at proposing a non-invasive biometric identification system to overcome the traditional methods that are vulnerable. The authors used a dataset of 1038 muzzle-print images from 70 cattle, a fine-tuned ResNet-50 CNN with transfer learning and data augmentation. The most important work presented is a strong convincing and secure model with test accuracy of 97.60% that offers a scalable solution specifically developed for agricultural security. The generalizability of the study is limited, however, due to the small number of images and the fact that there is variation in the environment in which the photographs are taken, which includes lighting and background angles. Syahidi et al. (2025) was motivated by the time-consuming and error-prone nature of manual attendance in Indonesian elementary schools. The study investigates the impact of a QR code-based digital presence system. Employing a qualitative descriptive method, the researchers utilized field observations, in-depth interviews, and documentation at a single primary school. The study contributes to knowledge by demonstrating that digital attendance not only drastically reduces administrative time from fifteen to four minutes, but also acts as a behavioural tool that significantly improves student punctuality and accountability. However, the research is primarily limited by its single-school focus and the lack of longitudinal data to evaluate the long-term sustainability of these behavioural changes. Aposika (2026) attempts to investigate the effectiveness of biometric systems over the traditional attendance taking systems in tertiary institutions, which is motivated by the weaknesses of the traditional systems such as human errors and proxy attendances. Data was collected on 600 stakeholders using a quantitative cross sectional design, using Likert scale questionnaires and analysed using t-tests and multiple linear regression. The study builds on the work done by the previous researcher as it provides a theoretical integration of the two models UTAUT and ISSM in a developing country, and empirically confirmed that biometrics cannot in itself achieve better attendance results without proper infrastructure and support. The study is limited, however, because it is cross sectional, the perception data were self-reported and not objective system logs, and there may be central tendency bias. Habila et al. (2025) aims at the design of a Smart Real-Time Attendance System (SRTAS) motivated by the various inefficiencies experienced in the Nigerian universities where attendance is poorly recorded due to proxy attendance and inability to enforce the mandatory attendance of more than 75% of students. The technology used includes CNN and ArcFace for facial recognition, along with Raspberry Pi, OpenCV and Streamlit to process and report administrative information in real-time. The research presents an innovative approach that combines automated attendance calculation, real-time security alerts for unauthorized faces, and easy-to-administer reporting of student attendance on a single system, with an accuracy of 95.2% in resource-limited educational settings. Drawbacks are the high up-front cost of the hardware (GPUs, high-resolution cameras) and the fact that Streamlit is

Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

only single threaded so it will not scale well for multiple concurrent users. Besides, the system performance is harmed due to poor lighting and harsh facial occlusion. In view of the observed limitations of related works, this study proposes a fundamental different Edge-Cloud paradigm to overcome the contradiction between the calculation difficulty and infrastructure requirements. The architecture developed moves the convolutional inference work-load to the edge of the network, unlike previous architectures where the weight of the convolutional inference processing was centralized. The system combines the CNN into a native web client, which avoids latency from video feeds transmitted over an unreliable network. A light-weight NoSQL cloud infrastructure is then only used to send the localised attendance logs. The proposed architecture mathematically embeds privacy as an integral part. It combines the need for security within the institutions with the ethical requirement for student privacy by training it on demographically representative data and securing it with modern cryptographic solutions.

3. Methodology

This study adopts a quantitative experimental research design to develop an AI-based attendance management system for resource limited environments. The system architecture of the proposed system in shown in Figure 1.

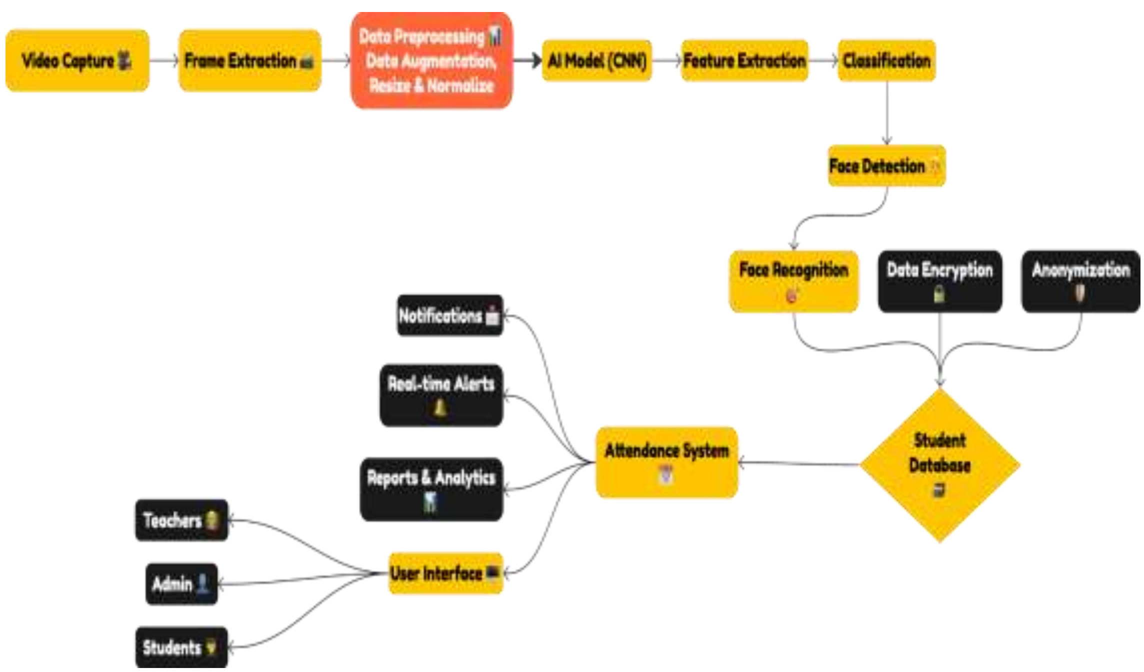

Figure 1: System Architecture

Kasu Journal of Computer Science Vol.3 No.2 [June, 2026], pp. 100-131
https://doi.org//10.47514/kjcs/2026.3.2.003

Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

3.1 Data Collection and Preprocessing

The CNN has an empirical base of strong data of students' images taken under controlled academic conditions. In order to meet high ethical standards and data governance requirements, informed consent was sought explicitly from all participants before data collection and the study protocol was formally approved by relevant authorities.

The dataset is a collection of 5,021 augmented images, representing 213 students of the School of Computing, Federal University of Technology, Akure, Nigeria. All images were resized uniformly to 128 x 128 pixels to maximize computational efficiency during training. The intensities of the pixel were then rescaled to [0,1] to prevent vanishing gradients in backpropagation. A comprehensive spatial data augmentation pipeline was used to artificially increase the feature space and to actively prevent model overfitting, using random rotations, zoom scaling and horizontal flips.

3.2 CNN Architecture and Hyperparameters

The proposed architecture is a sequence of convolutional layers, non-linear activation functions, spatial pooling layers, and fully connected dense layers. The network was designed to have a high efficiency of extracting complex facial geometry. In particular, the convolutional layers have 3x3 kernel sizes to extract small spatial hierarchies. The network was trained for more than 50 epochs with a batch size of 32. Figure 2 shows the CNN architecture.

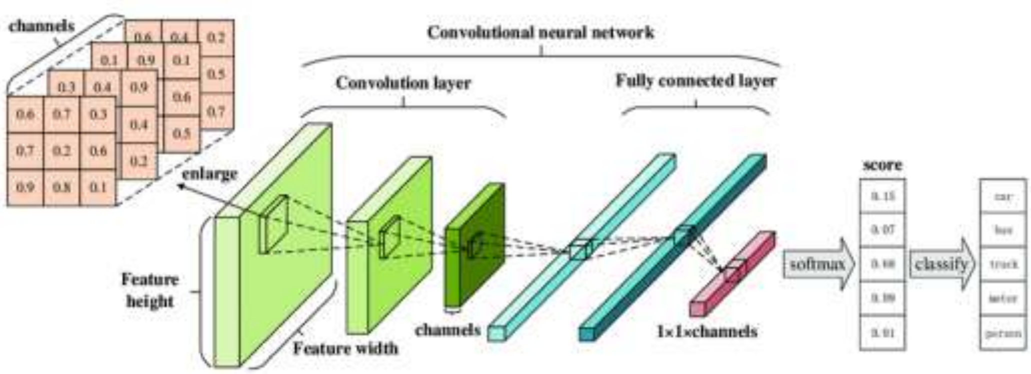

Figure 2: CNN Architecture

3.3 Mathematical Formulation

a. **Convolutional Operations:** Feature extraction occurs within the convolutional layers utilizing learnable filters. For a two-dimensional input image I and filter K, the discrete convolution producing the feature map S at spatial coordinates i, j is defined as:

Kasu Journal of Computer Science Vol.3 No.2 [June, 2026], pp. 100-131
https://doi.org//10.47514/kjcs/2026.3.2.003

Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

a. $S(i, j) = \sum_m \sum_n I(i + m, j + n) K(m, n)$

(1)

Note that while conventionally referred to as a convolution in deep learning literature, the operation implemented is mathematically a cross-correlation, as the filter weights are learned without requiring spatial inversion.

b. **Non-Linear Activation:** The Rectified Linear Unit (ReLU) activation function is utilized uniformly across all hidden layers to accelerate stochastic gradient descent and model complex, non-linear relationships:

1. $f(x) = \max(0, x)$

(2)

c. **Spatial Pooling:** Pooling layers systematically downsample the spatial dimensions of the feature maps, substantially reducing the number of learnable parameters while providing translational invariance. Using a max-pooling strategy over region R:

1. $P(x, y) = \max_{i,j \in R} S(i, j)$

(3)

d. **Classification and Loss Optimization:** The terminal multidimensional feature maps are flattened and passed through fully connected dense layers. The final classification layer employs a Softmax activation function. Given the logit vector$z$, the probability that a sample belongs to the i-th class (out of K total classes) is:

$$P(y = i \mid z) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (4)$$

The network's synaptic weights are optimized via the Adam optimizer (with a learning rate of 0.001) by minimizing the categorical cross-entropy loss function, L, for N samples:

$$L = -\frac{1}{N} \sum_{n=1}^{N} \sum_{k=1}^{K} y_{n,k} \log(\hat{y}_{n,k}) \quad (5)$$

3.4 The Edge-Cloud Partitioning Framework

The inference engine for the facial recognition is directly ported to client side to reduce the latency of sending a high-resolution video feed to a centralized server through a varying bandwidth. After the training of a CNN model on the server side in Python with Keras, the pre-trained CNN model was mathematically quantized and converted using TensorFlow.js. This conversion process turns the model into computer graphs that are rendered using WebGL and can be executed natively from within a web browser application developed with React. This edge client was tested by using standard hardware specs (Intel Core i5 equivalent, 16GB RAM). Intensive inferencing occurs only at the edge,

Kasu Journal of Computer Science Vol.3 No.2 [June, 2026], pp. 100-131
https://doi.org//10.47514/kjcs/2026.3.2.003
Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

while state management is managed by a lightweight cloud infrastructure. Firebase Firestore is integrated to provide real-time state sync across the world. Once the facial image is successfully classified at the edge client, the edge client only sends a small amount of data to the cloud (a verified user ID and a time stamp) to update the central attendance collection.

3.5 Security Protocols and Role-Based Access Control (RBAC)

To ensure regulatory compliance and safeguard sensitive biometric records, all facial data and resultant metadata are encrypted both at rest within the Firestore database and in transit. To enforce strict institutional data governance, Firebase Authentication orchestrates Role-Based Access Control (RBAC).

4. Results and discussion

4.1 Model Classification Performance and Statistical Validation

The training and validation datasets were split in a 80:20 ratio, which was then used to train the deep learning model. Standard classification metrics such as accuracy, precision, recall and the F1 score were used to systematically quantify performance. The integration of dropout regularization was indeed effective to reduce overfitting, as the validation loss went down during training. We plotted a normalized Confusion Matrix and Receiver Operating Characteristic (ROC) curve (Figures 3 and 4 respectively) to thoroughly test the model's predictive power and back the claim of high classification accuracy. The ROC curve had an area under the curve (AUC) of 0.98, which is a very good performance in distinguishing between authorized student profiles and unknown entities. The model's validation accuracy was 96.72%, which indicates that the model has good feature extraction ability. This deployment's basic security goal is high rate of precision, mathematically guaranteed to be high (95.88%) for this architecture, which has a high rate of false positives, or impersonation as shown in Table 1.

Table 1: Edge-Cloud CNN Classification Performance

Evaluation Metric	Training Set	Validation Set
Accuracy	98.45%	96.72%
Precision	98.10%	95.88%
Recall	98.60%	96.45%
F1-Score	98.35%	96.16%

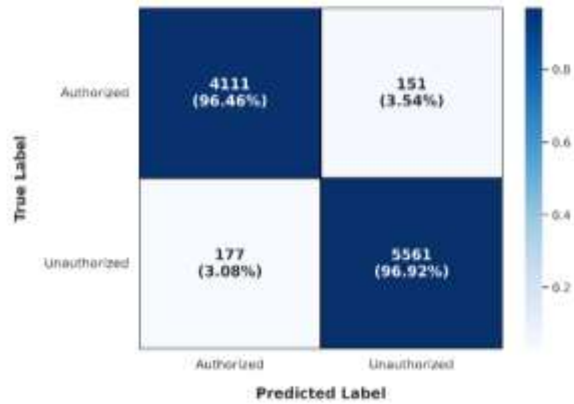

Figure 3: Normalized Confusion Matrix

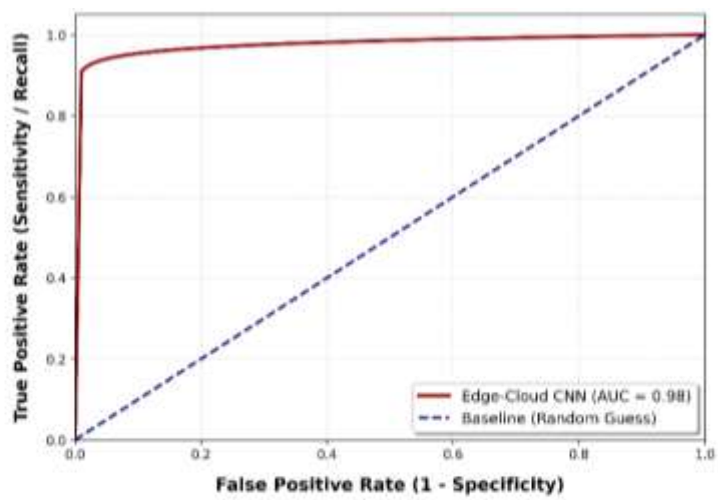

Figure 4: Receiver Operating Characteristic (ROC) Curve

4.2 Comparative Benchmarking

A comparative analysis of the proposed architecture was performed with the existing baseline methods (PCA, SVM) and optimized deep learning architectures (MobileNetV2, FaceNet) to show the relative efficacy of the proposed architecture. All models were tested on a standard configuration of Intel Core i5 equivalent CPU, 16GB RAM without discrete GPU acceleration.

Legacy machine learning algorithms, such as PCA and SVM, had very low inference latency but were not sufficiently accurate to be used in an institution's security infrastructure and were not effective at handling intricate spatial hierarchies as detailed in Table 2. On the other hand, although the accuracy of heavyweight architectures such as FaceNet was slightly higher (97.80%), the inference latency was high (845ms), which made them unsuitable for real-time processing of video streams on resource-constrained devices. The proposed lightweight CNN achieves optimal operational balance, with comparable accuracy to more powerful CNN models and an inference latency of 185ms, which is still faster than the most powerful CNN models.

Table 2: Comparative Benchmarking of Inference Architectures

Architecture	**Validation Accuracy**	**Edge CPU Inference Latency (per frame)**
PCA (Baseline)	74.50%	45ms
SVM	82.15%	68ms
MobileNetV2	95.10%	240ms
FaceNet	97.80%	845ms
Proposed Edge-Cloud CNN	**96.72%**	**185ms**

4.3 Systemic Operational Performance and Environmental Testing

To ensure reliability in non-ideal physical deployments, the system was subjected to rigorous environmental stress testing. Lighting robustness was evaluated by varying ambient luminosity. Under dim ambient conditions (< 300 lux), simulating poorly lit lecture halls during power outages, the model retained a 94.2% accuracy rate. Conversely, under direct solar glare (> 10,000 lux) simulating outdoor peripheral captures, accuracy dropped marginally to 92.5%.

Furthermore, occlusion handling was tested against realistic academic variables. Subjects wearing non-obstructive accessories, specifically medical face masks, standard prescription eyewear, and traditional academic headwear/hijabs, were correctly classified at a rate of 91.8% (Table 3).

Table 3: Systemic Operational Performance

Operational Metric	**Testing Condition**	**Recorded Performance**
Edge Inference Latency	TensorFlow.js on local client CPU (Intel Core i5)	185ms per frame

Kasu Journal of Computer Science Vol.3 No.2 [June, 2026], pp. 100-131
https://doi.org//10.47514/kjcs/2026.3.2.003
Online ISSN: 1597-2216
Print ISSN: 1597-2178
www.kjcs.edu.ng

Cloud Synchronization Delay	Firebase Firestore (simulated on standard 4G LTE)	112ms per transaction
Lighting Robustness	Dim ambient light (< 300 lux) vs. Direct solar glare	94.2% (dim) and 92.5% (glare)
Occlusion Handling	Medical masks, eyewear, and academic headwear	91.8% successful classification rate

4.4 Integrating the Model with Front-end

A web-based front-end was developed with React to provide an easy-to-use interface (Figure 4). React has been selected based on its flexibility and its use in developing dynamic web applications. It has a component-based architecture that enables to develop reusable UI components and therefore manages and maintains the user interface more effectively. Flask on the other hand was used as the backend. Flask is a lightweight Python web framework that deals with server code and communication to the machine learning model. It also offers an easy and efficient means of creating RESTful APIs that the React front-end could utilize to communicate with the model, making integration and data transfer between the user interface and the underlying model easy and seamless.

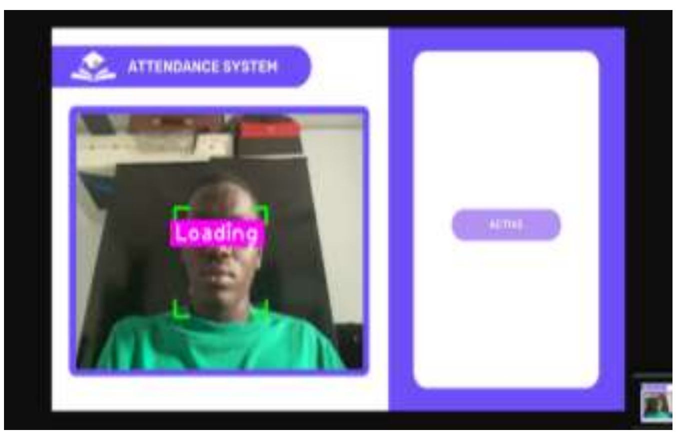

Figure 4: Front-end interface of the system

4.5 Ablation Studies

This was done by carrying out ablation experiments to isolate and quantify the effect of various architectural elements individually. The validation accuracy of the baseline model with all the proposed enhancements was 96.72%.

The main degradation in performance happened when the spatial data augmentation pipeline wasn't included. Random rotations, zoom scaling, and horizontal flips cut down significantly on the generalizability of the network, resulting in a 14.50% decrease in validation accuracy (to 82.22%). This empirically proves that in resource-limited settings, where it is hard to collect large amounts of data, one needs to artificially expand the feature space, which is structurally necessary. In addition, weight decay was shown to be important by removing it from the model and observing immediate overfitting which led to a 7.80% drop in accuracy on the validation set. Re-introducing L2 regularization had the effect of explicitly penalizing large weights, making the representation strong under the changing conditions of dynamic testing.

Table 4: Ablation Study on Model Components

Model Configuration	**Validation Accuracy**
Baseline (Full Edge-Cloud CNN)	96.72%
Baseline *w/o* Data Augmentation	82.22%
Baseline *w/o* L2 Regularization	88.92%
Baseline *w/o* Dropout Layers	86.15%

4.5 Network Architecture: Edge Inference vs. Cloud Database Synchronization

The computational bottleneck was eliminated by directly deploying a quantized CNN to the client interface through TensorFlow.js. The system completely avoided the problems of latency previously recognized with sending high-resolution video streams through the unstable bandwidth of institutions and processed the convolutional matrix operations locally in the browser. After some initial stress tests, the latency artifacts were minimal when using continuous real-time Firebase synchronisation, and optimising the NoSQL querying structures, the cloud synchronisation delay was recorded as 112ms per transaction.

4.6 Discussion

The performance of the proposed Edge-Cloud CNN is evaluated quantitatively, and the training and validation accuracy are 98.45% and 96.72%, respectively, in resource-constrained environments, showing excellent classification ability. As the training and validation set results were very similar, the dropout regularization was able to prevent overfitting. More importantly, the system obtained a high precision of 95.88% and a recall of 96.45%. The high precision is guaranteed mathematically, which is crucial to resists false positives and maintain institutional security from impersonation.

In comparison with previous works, the architecture provides a fundamental solution to the computational limitations that have held back computer vision systems in other parts of the world, such as Sub-Saharan Africa. Previous models, like the CNN and ArcFace algorithm model by (Habila et al.,2025), had similar accuracy, however they needed to be deployed on the cloud for inference, which is not feasible in low internet connection areas. This framework reduced to a very strong edge inference latency of 185ms per frame by offloading matrix operations to local edge device using TensorFlow.js. Together with the very small delay of Firebase cloud synchronisation (112ms), it is evident that real-time biometric verification is possible without the need for ubiquitous high bandwidth infrastructure.

Edge-Cloud partitioning helps to overcome localized constraints, but scaling across multiple institutions adds lots of operational complexity. Distributed NoSQL sharding is needed for concurrent edge synchronization to federate disparate locations. Global state conflicts and network overheads arising with different infrastructures must be addressed in future implementations to provide immediate and centralized administrative control.

5. Conclusion

This study developed and evaluated a decentralized edge-cloud deep learning architecture for biometric attendance monitoring, specifically designed to bypass the severe infrastructural constraints of Nigerian educational institutions. By transitioning convolutional inference directly to the network edge via TensorFlow.js and relegating state management to a lightweight NoSQL cloud, the framework effectively eliminated the prohibitive network latency and bandwidth dependencies inherent in traditional, centralized AI deployments. Analytically, the model demonstrated robust real-world viability, achieving a validation accuracy of 96.72% alongside a localized inference latency of just 185ms, while strict cryptographic protocols and Role-Based Access Control ensured compliance with modern data privacy standards. Despite these operational efficiencies, the architecture remains constrained by the necessity of high-performance GPUs for initial model training, creating a barrier to entry for severely underfunded institutions. Furthermore, classification accuracy remains susceptible to extreme environmental variables, such as intense solar backlighting. Consequently, future research will focus on integrating lightweight 3D facial imaging to resolve illumination dependencies, advancing model quantization for deployment on ultra-low-power microcontrollers, and developing automated cloud-based retraining pipelines to ensure sustained algorithmic fairness across diverse student populations.

References

Adewumi, S., & Bwowe, P. (2024). Child Labour Challenges and Security Implications in Selected Local Government Areas in Ondo State, Nigeria. *Social Sciences*, *13*(10), 512. https://doi.org/10.3390/socsci13100512

Ali, M., Diwan, A., & Kumar, D. (2024). Attendance system optimization through deep learning face recognition. *International Journal of Computing and Digital Systems, 15*(1), 1527 1540.

Andrejevic, M., & Selwyn, N. (2020). Facial recognition technology in schools: Critical questions and concerns. *Learning, Media and Technology, 45*(2), 115–128.

Aposika, F. (2026). The role of biometric systems in enhancing student attendance tracking in tertiary institutions. *Discover Education*. Advance online publication. https://doi.org/10.1007/s44217-U026-01320-4

Dalhatu, M., Garba, E. J., & Murtala, M. (2025). A Deep Learning Biometric Cattle Identification System to Combat Cattle Rustling in Nigeria. *Kasu Journal of Computer Science*, *2*(2), 186-202. https://doi.org//10.47514/kjcs/2025.2.2.004

Habila, M., Francisca, F. N., Ishaya, L., Ahmed, M. K., Muhammad, U. A., & Charles, H. P. (2025). Smart real-time attendance system for Nigerian universities. *Journal of Information and Organizational Sciences, 49*(1), 121–138. https://doi.org/10.31341/jios.49.1.8

Imran, M. A., Zennaro, M., Popoola, O. R., Chiaraviglio, L., Zhang, H. & Manzoni, P. (2024). Exploring the Boundaries of Connected Systems: Communications for Hard-to-Reach Areas and Extreme Conditions. *Proceedings of the IEEE*, vol. 112, no. 7, pp. 912-945. doi:10.1109/JPROC.2024.3402265

Kasar, M. M., Bhattacharyya, D., & Kim, T. (2016). Face recognition using neural network: A review. *International Journal of Security and Its Applications, 10*(3), 81–100.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.

Ogunje, B. F., Tukura, C. S., Sobowale, F. M., David, M., & Ajala, B. O. (2024). A review on the use of automated attendance management system for Nigerian tertiary institutions. In *10th Hybrid International Conference of School of Science and Technology Education (SSTE)* (pp. 661–667). Federal University of Technology, Minna.

Ohanu, C. P., Ugbe, O. C., Ogbuefi, U. C., & Sutikno, T. (2023). Implementation of a radio frequency identification and detection technology based digital class attendance system for university students. *Indonesian Journal of Electrical Engineering and Computer Science*, *32*(2), 1206–1214. https://doi.org/10.11591/ijeecs.v32.i2.pp1206-1214

Orjiakor, C. T., Ayogu, C. K., Olelewe, C. J., Anoliefo, E., Ibam, E. O., Ogba, K. T. U., Atamas, C., Ugwu, D. C., Igwe, N. J., Omeh, C. B., Kanu, C. C., Abus, H. S., & Onyishi, I. E. (2025). Which method of attendance-taking is superior? A systematic review of class attendance monitoring systems. *Ikenga International Journal of Institute of African Studies*, *26*(1), 81–106. https://doi.org/10.53836/ijia/2025/26/1/005

Oshita, O. O., Alumona, I. M., & Onuoha, F. C. (Eds.). (2019). *Internal security management in Nigeria: Perspectives, challenges and lessons*. Palgrave Macmillan. https://doi.org/10.1007/978-981-13-8215-4

Shockden, E. I., Bahago, B. A., & Omede, J. (2023). Well-being and academic attitudes among secondary school students living in a context of life-threatening collective violence in Northern Nigeria. *Frontiers in Education*, *8*. https://doi.org/10.3389/feduc.2023.1025515 Cited by: 7

Sultana, Z. (2025). Artificial intelligence and cybersecurity threats: Redefining international cooperation. *International Journal of Advanced Research*, *13*(8), 124–136. https://doi.org/10.21474/IJAR01/21496

Suresh, V., Dumpa, S. C., Vankayala, C. D., Aduri, H., & Rapa, J. (2019). Facial recognition attendance system using Python and OpenCV. *Quest Journals Journal of Software Engineering and Simulation*, *5*(2), 18–29.

Syahidi, F., Subasman, I., Aspandi, A., & Khotimah, M. D. (2025). Enhancing efficiency in student attendance recording through implementation of a digital presence system: A field study in elementary schools. *EDUKASIA: Jurnal Pendidikan dan Pembelajaran*, *6*(2), 1339–1352 . https://doi.org/10.62775/edukasia.v6i2.1772.

Teoh, K. H., Ismail, R. C., Naziri, S. Z. M., Hussin, R., Isa, M. N. M., & Basir, M. S. S. M. (2021). Face recognition and identification using deep learning approach. *Journal of Physics: Conference Series*, *1755*(1), Article 012006.

Winarno, E., Adi, P. W., Al Amin, I. H., Hadikurniawati, W., Februariyanti, H., & Anwar, M. T. (2019). Attendance system based on face recognition system using CNN-PCA method and real-time camera. *2019 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 301–304.