AKATHON4AIoT REPORT:
Multi-edge Capable Attendance System

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Executive Summary

Tracking student attendance is often used to evaluate academic performance. However, the manual tracking of student attendance by teachers is both time-consuming and labor-intensive. This report demonstrates a method for a Student Attendance Checking System utilizing GhostFaceNets, a lightweight face recognition model introduced in 2023. The model size is less than 20MB and does not require a GPU for inference. Furthermore, the system in this report can be used on multiple platform interfaces (e.g., edge devices, mobile, tablet), allowing students to use their personal devices to check their attendance.

I. Introduction

In the past few years, the global landscape of computer security technology has been significantly shaped by the swift advancement of face recognition systems. This technology, with its myriad of applications, has become increasingly prevalent in areas such as public safety (Andrejevic & Selwyn, 2020) and civil economy (Fussey, et al., 2021). Despite its critical role in maintaining productivity, attendance tracking in many organizations remains a manual or inefficient technology-integrated process. These traditional approaches are not only labor-intensive and time-consuming but also prone to human error and manipulation. Examining the existing fingerprint-based attendance system, our team finds out that it possesses an approximate error rate of 5%. This rate is subject to escalation due to factors such as improper placement of fingerprints, moisture presence, or thin fingertip surfaces (Abdulkadhim, 2020). During high-traffic periods, this system may encounter difficulties in capturing accurate readings due to the hurried nature of individuals, thereby significantly impacting the effectiveness of attendance verification. Conversely, the card-based attendance system, which utilizes RFID or QR Code scanning, is susceptible to instances of proxy attendance, resulting in potentially inaccurate timekeeping outcomes.

In the context of educational institutions like Swinburne University, inaccurate attendance records can lead to misjudgements about student engagement and performance (Kar, et al., 2012), potentially impacting the overall quality of education. Recognizing the necessity for an innovative approach, particularly within the educational sector, and aiming to address the shortcomings of traditional systems, this report suggests the adoption of face recognition technology utilizing GhostFaceNets. GhostFaceNets is a lightweight and effective Convolutional Neural Network (CNN) or a Deep Learning framework. This framework's strength lies in its lightweight, end-to-end approach and state-of-the-art feature extraction and selection, supporting multi-edge extensibility and eliminating costly computational processing. The main contribution of this report can be listed below:

1. Compared to other face recognition systems, our model takes pride in surpassing the performance of machine learning models like Viola-Jones (Wati, et al., 2021) or Support Vector Machine (SVM) (Yang & Han, 2020) in indoor environments. These models have accuracy rates of 75% and 85% respectively, while our model boasts an accuracy of 93.3%.
2. Furthermore, our solution presents enhanced flexibility and adaptability across various university settings, owing to its ability to support Raspberry Pi, Web, and Mobile applications.

The report is organized as follows. Second and third section will review the current issue of attendance checking at FPT University, Swinburne Vietnam and meticulously detail our prosed solution in terms of technology. The next section will focus on our methodology. Subsequently, section IV presents the results and extends the analysis. Finally, we discuss about the future works to improve the drawbacks of our model and conclude the paper in section V.

II. Problem Statement

In many organizations, the process of attendance tracking remains a manual and labor-intensive task, despite it being one of the key factors in terms of tracking the productivity belonging to the associates of the aforementioned groups (Alagasan, et al., 2021). This outdated method not only consumes valuable time but also requires significant human effort (Dassanayake & Wanniarachchi, 2021).

In the context and environment of universities and other educational institutions, like our own Swinburne University of Technology, taking attendance is often a crucial step in the undertaking of units, as several mandatory tasks within units, such as the ability to take the Final Test, the unlocking of certain documents, etc. become inaccessible if a certain attendance percentage threshold is not met. Other situations involve taking away the total score of a unit if a student is absent for numerous days (Moores, et al., 2019). Unless the handicap of manual attendance cannot be solved, several problems of inconvenience, incompetence, or lack of knowledge can lead to inaccuracies in the grades or other results of students.

Recognizing the need for a more efficient solution, we propose the implementation of an automated AI-powered attendance checking system based on face recognition technology. This not only saves time for both employees and administrators but also ensures a more secure and efficient attendance tracking system. With this modernized approach, organizations, and in our case the University and potentially other educational faculties, can focus more on their core tasks while enjoying the benefits of enhanced productivity and efficiency (Ali, et al., 2022). Since attendance takes up a noticeable amount of the time held in lectures, inefficient processes of taking attendance can lead to lecturers wasting precious time, or even loss of attention and interaction within the classroom. This can lead to inaccurate conclusions and evaluation of an educational institution's teaching quality. Khan, Jhanjhi and Humayun (2018). Our solution aims to rid the time-consuming nature of manual attendance by offering an automated solution to this problem that promotes ease of us and self-awareness. Since attendance takes up a noticeable amount of the time held in lectures, inefficient processes of taking attendance can lead to lecturers wasting precious time, or even loss of attention and interaction within the classroom. This can lead to inaccurate conclusions and evaluation of an educational institution's teaching quality (Khan, et al., 2018).

III. Proposed Solution

In light of this supposed problem, we have decided to invest in the development of A Deep Learning Model that can Recognize Faces. This model can be utilized to automate the attendance process through the application of Face Recognition, which is developed and powered by a lightweight Deep Learning model that extracts visual features from facial images. The trained model has high accuracy and is trained using a large dataset. Additionally, another implemented feature is identity matching, done by applying Clustering and other Machine Learning algorithms. The results of these functionalities are returned and displayed on our specifically designed cross-platform UI that supports multiple devices for easier deployment and usage on multiple edge devices.

IV. Methodology

A. Why GhostFaceNets as base for the model?

This solution is intended to be used in workplaces, schools, and other facilities that would need a secure, fast and efficient way to automatically check for attendance. So, we chose to make the solution edge-capable by making the base of the model GhostFaceNets - known for its speed and accuracy. Then it can be deployed anywhere using an appropriate wrapper, which we chose Docker.

Some example deployment can be:

- Docker container with the solution deployed on the company server with a separate node that has also has an internal website for the attendees to use. Then all the edges only need to login via the website to check attendance.
- Or the Docker container can be deployed on all the edges, ensuring the ability to check attendance regardless of black-outs or loss of internet connection/ server downtime, the edge can then upload the attendance data whenever the connection has been remade, with the bonus of knowing which user has logged on using which edge.

B. Why do we choose Docker?

We wanted this solution to be portable and works flawlessly everywhere, so we choose Docker, in tandem with this, we also chose the slim Debian image as base for the container to ensure the lowest mount of RAM taken possible so we can deploy on edge devices like a Raspberry Pi 3B easily.

Subsequently, by using Docker, this allows the client to make this into a standalone API which they can then add other functionality and build a system fit for their own use-case.

V. Evaluation Results & Analysis

The face recognition application is evaluated using a dataset of popular Vietnamese celebrities, known as the VN-Celeb dataset. This dataset consists of 4720 facial images, each represented by a 512-dimensional embedding vector extracted using the GhostFaceNets model. The application utilizes the "mean face enhancement" method, which involves computing a single representative embedding vector for each unique identity by averaging the embeddings of all facial images belonging to that identity.

As depicted in Figure 1, the application's face recognition capabilities are assessed using various metrics, including accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic (ROC) curve.

```
>>>> [base info] embs: (4720, 512) imm_classes: (4720,) register_ids: (1000,)
Evaluating: 100%|██████████| 1000/1000 [00:03<00:00, 255.82it/s]
saving vector đại diện tại:  /content/drive/MyDrive/jupyterNotebook/root_embs/processed_1000embedding.npz
Shape of similarity matrix between images and classes: (4720, 1000)
register_ids shape:  (1000,)
self.imm_classes shape:  (4720,)
Shape of positive prediction conditions array: (4720, 1000)
Shape of positive prediction distances array: (4720,)
(4715280,)
Accuracy:  0.9328389830508474
Precision: 0.8363040360581848
Recall: 0.8648305084745763
F1 Score: 0.8503280908238725
```

Figure 1: The face recognition application metrics

The evaluation results demonstrate that the face recognition app achieves an overall accuracy of 0.9328389830508474 or approximately 93.28%. This accuracy metric represents the proportion of correctly classified instances out of the total number of instances in the dataset, reflecting the application's strong performance in recognizing faces accurately. The precision score of 0.8363 indicates that approximately 83.63% of the positive predictions made by the app are correct, while the recall score of 0.8648 suggests that the app correctly identified 86.48% of the actual positive instances in the dataset. The F1-score, which is the harmonic mean of precision and recall, stands at 0.8503. This score provides a balanced measure of the app's performance, taking into account both precision and recall. The higher the F1-score, the better the app's ability to correctly identify true positives while minimizing false positives and false negatives.

Furthermore, the ROC curve graphically represents the trade-off between the true positive rate (TPR) and the false positive rate (FPR) at different classification thresholds.

	1e-06	1e-05	0.0001	0.001	0.01	0.1
TPR	0.500212	0.686017	0.841314	0.935593	0.98178	0.998517

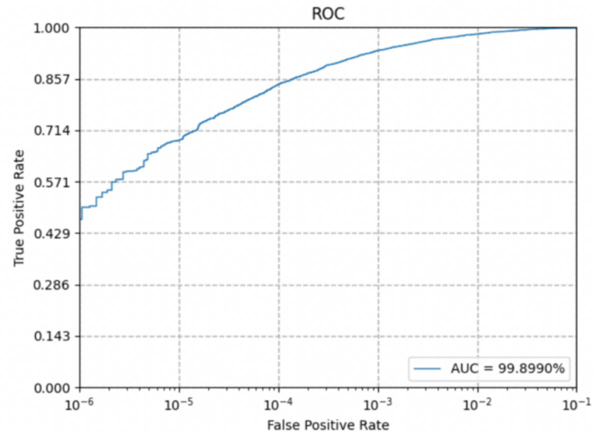

Figure 2: The ROC curve

An ideal ROC curve would appear as a straight line along the top-left corner of the graph (FPR = 0, TPR = 1). The closer the actual ROC curve gets to this ideal line, the better the model's performance (Bhandari, 2020). In Figure 2, our curve leans significantly towards the top-left corner, indicating strong performance by the GhostFaceNets model. This suggests the model can effectively distinguish between positive and negative cases with a minimal number of false positives.

Another metric for evaluating a model's performance is the Area Under the Curve (AUC), displayed in the bottom right corner of the screenshot. The AUC value (99.8991% in this case) quantifies the overall effectiveness of the model. It represents the likelihood of the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance. The high AUC in the result indicates that the GhostFaceNets model is highly adept at differentiating between positive and negative examples within the dataset.

GhostFaceNets stands out for its lightweight design in the world of face recognition models. This translates to faster processing time, lower power consumption, and the ability to run on devices with limited resources. However, it is important to understand that the app's performance may be influenced by factors such as image quality, occlusion, extreme variations in facial expressions or poses, and the diversity and representativeness of the dataset used for training and evaluation.

VI. Future Works

The current work is focused on developing the facial recognition model and deploying it across multiple devices.

In further work, to apply it to the university scenario, the system needs to develop a function that detects the geolocation of students to satisfy the requirement of check-in by their own devices. Additionally, the system needs to be developed to record the entry time of students and create a list of students who have checked in, storing it in a database. The accuracy of the face recognition model is intended to be increased in the future. Moreover, authors need to collaborate with Swinburne Vietnam Alliance Program to update student check-in statuses on the portal website and allow university staff to view the check-in status of all students in the front-end.

VII. Conclusion

This report has presented an innovative approach to address the issue of traditional attendance records in educational institutions. Our solution, which leverages the power of GhostFaceNets, has demonstrated superior performance compared to traditional machine learning methods in terms of accuracy in in-door environments. The work has also focused on deploying our model across multiple devices adapting to different educational scenarios. However, there are rooms for improvement such as refining and expanding system's capabilities with geolocation detection, entry time recording, and database integration for logging. We also seek for enhancements of our system against deepfake or cheating attempts. Our team looks forward to a collaboration with Swinburne Vietnam Alliance Program to update student check-in status via our product.

VIII. Acknowledgement

This report stands as a testament to the collaborative efforts of a group of Artificial Intelligence students, guided by Dr. Eric Le, as part of a comprehensive Deep Learning course. Our innovative product was meticulously planned, deployed, and tested thanks to the unwavering support of Swinburne Vietnam, an alliance program between FPT University, Vietnam and Swinburne University of Technology, Australia. Our work underscores the potential of Artificial Intelligence in transforming traditional systems and processes, paving the way for more efficient and effective solutions, especially in the realm of education and technology.

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