ENHANCING STUDENT ATTENDANCE MANAGEMENT USING FACE RECOGNITION WITH MULTI-TASK CASCADED CONVOLUTIONAL NEURAL NETWORKS: A CASE STUDY AT FACULTY OF INFORMATION TECHNOLOGY, HAI PHONG UNIVERSITY

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Abstract: Face recognition is a pivotal domain within computer vision, focused on verifying and identifying individuals using images or videos. People find applications across diverse fields, including security systems, biometrics, attendance tracking, and timekeeping. Significant advancements in face recognition techniques have been achieved, with deep learning and Neural Network approaches demonstrating superior accuracy. This paper presents the development of a face recognition system designed for student attendance monitoring in classrooms, utilizing the Multi-task Convolutional Neural Network (MTCNN) model. This advanced recognition technology offers rapid, accurate, and efficient identification or verification. As a result, the use of facial recognition systems in educational institutions has garnered considerable interest among administrators for its convenience, the ability to deliver swift and reliable solutions for tracking and recording student attendance.

Keywords: Face detection; Face recognition; Student attendance; CNN; MTCNN.

TĂNG CƯỜNG CÔNG TÁC ĐIỂM DANH SINH VIÊN SỬ DỤNG NHẬN DIỆN KHUÔN MẶT VỚI MẠNG NƠRON TÍCH CHẬP ĐA NHIỆM: ỨNG DỤNG TẠI KHOA CÔNG NGHỆ THÔNG TIN, TRƯỜNG ĐẠI HỌC HẢI PHÒNG

Tóm tắt: Nhận diện khuôn mặt là một lĩnh vực quan trọng trong thị giác máy tính tập trung vào việc xác minh và nhận dạng cá nhân thông qua hình ảnh hoặc video. Công nghệ này được ứng dụng rộng rãi trong nhiều lĩnh vực bao gồm hệ thống an ninh, sinh trắc học, theo dõi điểm danh và quản lý thời gian. Hiện nay phương pháp học sâu và mạng nơ-ron thể hiện độ chính xác vượt trội và có nhiều tiến bộ đáng kể trong kỹ thuật nhận diện khuôn mặt. Bài báo này trình bày việc phát triển hệ thống nhận diện khuôn mặt hỗ trợ quản lý điểm danh sinh viên trong lớp học sử dụng mô hình mạng nơron tích chập đa nhiệm (MTCNN). Công nghệ nhận diện tiên tiến này cung cấp khả năng nhận dạng hoặc xác minh nhanh chóng, chính xác và hiệu quả. Do đó, việc áp dụng hệ thống nhận diện khuôn mặt trong các cơ sở giáo dục đã thu hút sự quan tâm đáng kể từ các nhà quản lý nhờ tính tiện lợi và khả năng cung cấp các giải pháp nhanh chóng, đáng tin cậy trong việc theo dõi và ghi nhận điểm danh sinh viên.

Từ khóa: Phát hiện khuôn mặt; Nhận diện khuôn mặt; Điểm danh sinh viên; CNN; MTCNN.

1. INTRODUCTION

Traditional attendance methods remain essential in universities and colleges. However, many departments continue to rely on manual processes, such as calling out students' names, which is both time-consuming and disruptive to the duration and quality of classes. To address these challenges, numerous institutions have adopted advanced techniques for recording attendance, including RFID cards [1], iris recognition [2], and fingerprint recognition. Despite their benefits, these systems often require queuing, making them inefficient and susceptible to forgery.

Face recognition, a robust biometric identification technology, offers an effective alternative. It is both user-friendly and highly resistant to fraud. A face recognition system operates in two stages: face detection and face recognition. The latter involves a 1:1 matching process, where an image captured by a camera or webcam is compared against a database of stored face images, referred to as face queries [3].

This research focuses on developing a student attendance management system utilizing the Multi-task Convolutional Neural Network (MTCNN) model. By implementing this system, attendance processes in classrooms can be simplified, expedited, and made more accurate and efficient. The proposed solution enhances the learning and teaching environment for both students and instructors while enabling schools to effectively monitor and manage attendance records [4-6].

2. RELATED WORKS

The use of face recognition and machine learning algorithms in student attendance systems has garnered significant attention in recent years due to their potential to enhance efficiency and accuracy. Below is an overview of relevant studies and developments in this domain:

- *Face Recognition in Attendance Systems*: Numerous studies have explored the application of face recognition technologies for automating attendance management. For instance, Zhang and Liu [7] proposed a real-time attendance system using deep learning-based face recognition techniques, demonstrating high accuracy under controlled environmental conditions. Similarly, Patel and Sharma [8] highlighted the integration of OpenCV and Haar Cascades for facial detection, which enabled an affordable yet effective attendance tracking solution. Despite the promising results, challenges such as illumination variation, facial occlusions, and the need for robust algorithms to handle diverse student populations remain key areas of focus in the literature.

- *Machine Learning for Enhanced Accuracy*: Machine learning algorithms have significantly improved face recognition's performance by leveraging models like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and transfer learning techniques. A study by Chen and Li [9] employed CNN-based architectures for feature extraction and classification, achieving a notable improvement in recognition rates compared to traditional methods. Moreover, ensemble learning approaches have been utilized to combine multiple algorithms, further enhancing robustness.

- *Hybrid Approaches*: Recent advancements have also integrated face recognition with other biometric modalities, such as fingerprint or voice recognition, to create hybrid attendance systems. For example, Kumar and Singh [10] developed a multi-modal attendance tracking system combining face and iris recognition to achieve higher accuracy and security. Additionally, integrating Internet of Things (IoT) technologies with machine learning has been explored to enable real-time attendance tracking and data synchronization across distributed environments.

- *Deployment Challenges*: The adoption of face recognition-based attendance systems is not without limitations. Privacy concerns, data security, and computational requirements are commonly discussed in the literature. Ahmed and Lopez [11] conducted a survey on ethical implications, emphasizing the importance of anonymization and compliance with regulations such as GDPR for ensuring user trust. Furthermore, edge-computing-based implementations have been proposed to mitigate the computational burden associated with face recognition algorithms while maintaining real-time performance.

- *Comparison with Traditional Systems*: Comparative analyses between automated and traditional attendance systems underscore the advantages of face recognition-based solutions in terms of time efficiency and error reduction. For example, Gupta and Mehta [12] reported a significant decrease in human errors and improved scalability when transitioning from manual attendance recording to AI-driven solutions.

The integration of advanced machine learning models like Generative Adversarial Networks (GANs) to improve data augmentation for diverse datasets has been identified as a promising avenue. Furthermore, Wang and Yang [13] suggested the potential of federated learning to enhance model training without compromising data privacy, making it a suitable candidate for educational institutions.

The implementation of face recognition for student attendance systems in Vietnam has attracted significant attention in both academic and practical spheres. Several Vietnamese researchers and technologists have investigated the application of machine learning and AI-based face recognition systems to replace traditional attendance tracking. This research has focused on algorithm optimization and customized models. Nguyen et al. [14] utilized convolutional neural networks (CNNs) to improve face recognition accuracy under Vietnamese environmental conditions such as lighting variations and diverse facial features. The customized models, developed and fine-tuned for Vietnamese facial datasets, have outperformed general-purpose systems in terms of precision and recall [15, 16]. A system integrating deep learning algorithms for face detection and recognition with IoT devices was implemented at Hanoi University of Science and Technology [17]. This system successfully automated attendance in large lecture halls. Ho Chi Minh City University of Technology deployed a prototype system incorporating a cloud-based facial database for real-time recognition and attendance logging. Results showed increased efficiency compared to manual methods, although technical issues like network dependency were noted [18]. Studies by Tran et al. [19] compared face recognition systems to RFID card-based systems and manual attendance methods, revealing higher accuracy with reduced errors caused by impersonation or proxy attendance, faster processing times, and real-time updates. Face recognition systems had higher initial costs but lower long-term maintenance expenses than RFID-based setups.

3. SYSTEM MODEL PROPOSAL

The student attendance process involves four key steps: data collection, face detection, face recognition, and attendance marking [14-20]. During the data collection phase, approximately 50 images of each student are captured from various angles. These images are stored in a dataset alongside relevant details such as student ID (auto-generated), full name, date of birth, and phone number.

At the beginning of each class, students present themselves before a classroom camera, where their faces are detected and compared against the images in the dataset. Upon identifying a match, attendance is automatically recorded for the corresponding student. At the end of the class, a list of absentees can be generated and sent to the respective instructors for review.

The model of the proposed system is shown in the following Figure 1. Typically, this process can be divided into four stages.

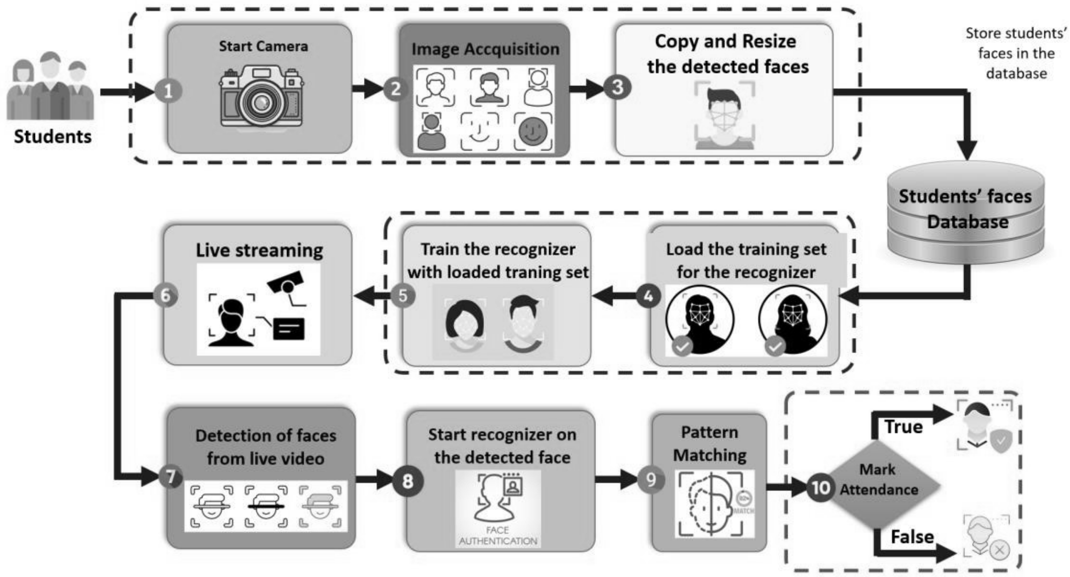


Figure 1. Our student attendance system model proposed

3.1. Data Collection

In the data collection phase, each student's photos are captured from various angles, resulting in approximately 50 images per individual. These images are saved in separate, numbered folders for organizational purposes. To enhance accuracy, preprocessing is applied to mitigate the effects of rotation and variations in lighting intensity. The images are also converted from RGB to grayscale to simplify subsequent processing.

In addition to photo collection, students provide their personal information, including student ID, full name, date of birth, department, class, phone number, and email address. This data is stored alongside the image dataset for comprehensive record management.

3.2. Face Detection with MTCNN

The face detection process identifies faces in images or video frames using the Multi-task Convolutional Neural Network (MTCNN), which operates through three network layers: P-Net, R-Net, and O-Net [11] (see Figure 2) [4-6].

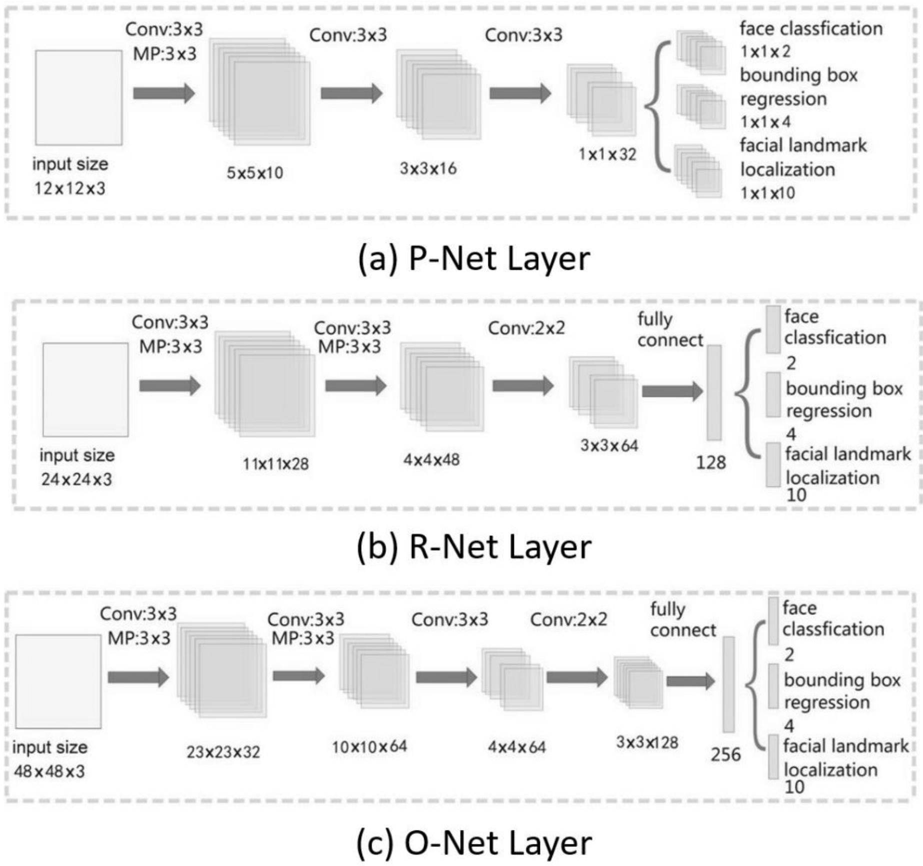


Figure 2. The Multi-task Convolutional Neural Network (MTCNN) layers [5]

Step 1: P-Net. At this stage, the system addresses scenarios where a photo may contain multiple faces of varying sizes. To detect all faces, MTCNN employs an Image Pyramid approach, where the original image is resized into a series of scaled copies, ranging from large to small. This allows for effective detection of faces across different dimensions.

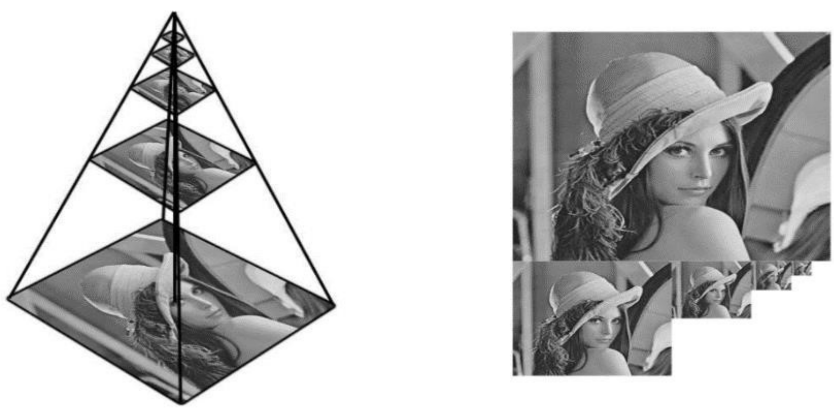


Figure 3. Images are resized to different sizes [6]

A kernel of 12x12 pixels with a stride of 2 pixels is used to scan the entire image and its resized versions. Sub-regions extracted from these resized images are passed through the Proposal Network (P-Net), which outputs a set of bounding boxes for each sub-region. Each bounding box contains the normalized coordinates of the four corners (ranging from 0 to 1) and a confidence score indicating the likelihood of a face being present. By leveraging the Image Pyramid and fixed kernel size, this approach enables the network to detect faces of varying scales with high precision, regardless of the face size or position within the image (see Figure 3).

Step 2: R-Net. The Refine Network (R-Net) builds upon the work of the P-Net by further refining the detected bounding boxes. An important addition in this step is the use of a padding technique, which adds zero-pixels to areas where bounding boxes extend beyond the boundaries of the image. This ensures that all bounding boxes remain within a consistent frame for processing. The bounding boxes are then resized to a fixed dimension of 24x24 pixels, effectively treating each as a kernel. These resized regions are passed through the R-Net, which analyzes the input and outputs updated coordinates for the bounding boxes. These refined bounding boxes, containing more precise face localization data, are subsequently passed to the next network layer, the O-Net, for further processing.

Step 3: O-Net. The final stage of the system is the Output Network (O-Net), which refines the results from the previous layers. Similar to the R-Net, the O-Net processes resized input images, but at a higher resolution of 48x48 pixels. This allows for more precise detection and classification.

The O-Net generates a comprehensive output with the following components:

1) Bounding Box Coordinates (out[0]): Precise localization of the detected face within the image.

2) Facial Landmark Coordinates (out[1]): Positions of five key facial landmarks, including the two eyes, the nose, and the two corners of the mouth.

3) Confidence Score (out[2]): A probability value indicating the likelihood that the bounding box contains a face.

These results are compiled into a structured dictionary, with the bounding box coordinates, facial landmarks, and confidence scores as distinct keys. This detailed output enables robust face detection and prepares the data for subsequent recognition processes.

After processing through the MTCNN network, facial regions are extracted and organized into separate folders for each student. Each facial image is then encoded into a 128-dimensional feature vector using the Face_recognition and dlib libraries. These feature vectors, as illustrated in the figure below, serve as unique biometric representations of individual faces.

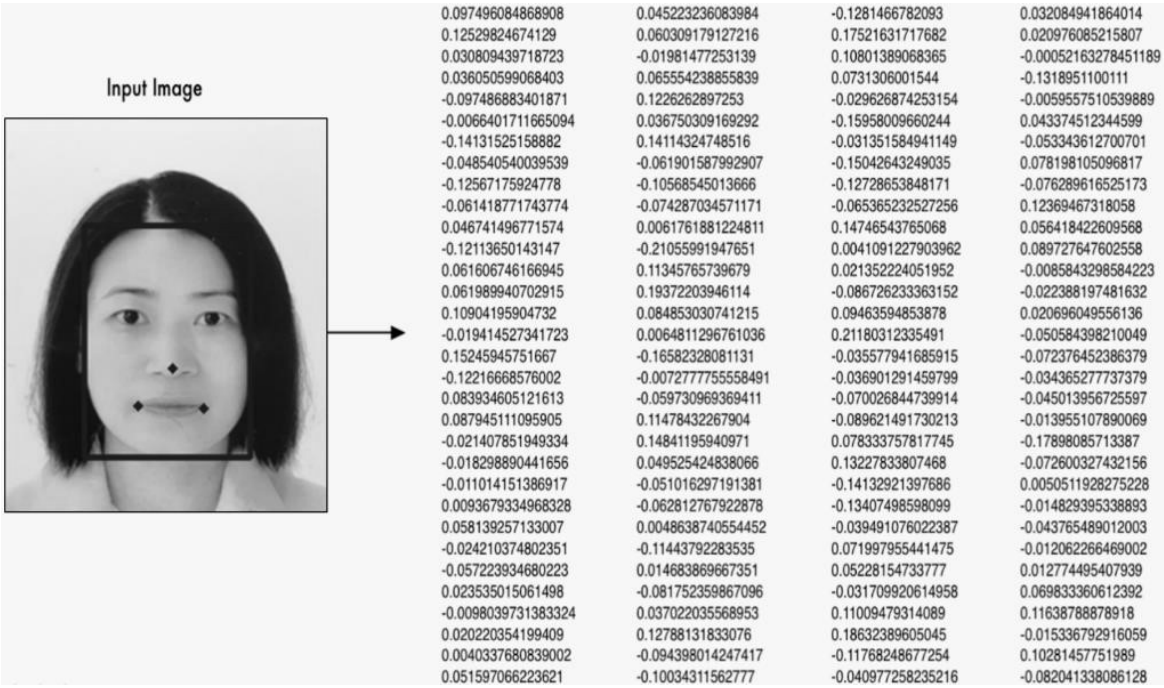


Figure 4. Face is encoded into 128-dimensional vector with sample image [6]

In face recognition, the 128-dimensional feature vector is an efficient way to store and represent the key characteristics (features) of a face. This numerical vector encodes each dimension (or component) as a different feature of the face. Each value within the vector carries information about the geometric and structural characteristics of the face, enabling the system to distinguish between different faces even in the presence of minor variations in lighting, angle, or expression. For example, models like FaceNet utilize a final "embedding" layer to convert facial features (derived from pixel images) into a fixed-size vector, typically 128 dimensions. This process reduces the size of the data while retaining all the necessary information for accurate recognition.

Each dimension of the 128-dimensional vector represents a significant facial feature, including:

- *Shape of Eyes, Nose, and Mouth*: Geometric features, such as the position, size, and ratio of facial components (eyes, nose, mouth), are encoded as numerical values. For instance, the first dimension may represent the eye length, the second dimension the distance between the eyes and nose, and so on.

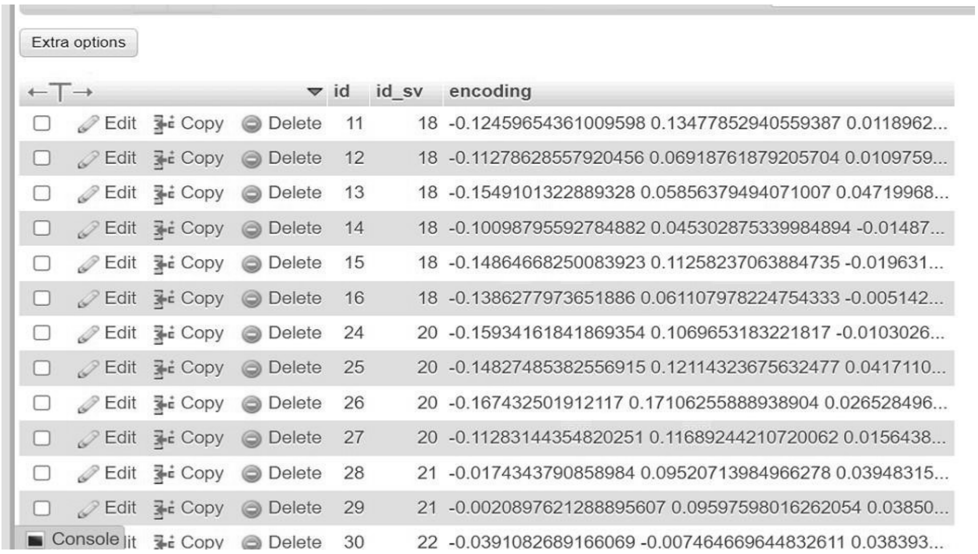
- *Face Shape Features*: Each person's face has a unique structure, including the outline of the chin, cheekbones, and other defining features. These structural characteristics are encoded into the vector, with values reflecting the proportions and overall shape of the face.

- *Facial Expressions*: Some models are capable of learning features related to facial expressions, such as smiling, frowning, or other emotional displays. Despite variations in expressions, deep learning models extract robust facial features that remain consistent across different situations.

- *Lighting and Viewing Angles*: The vector may also encode features related to how light interacts with the face and how the face is viewed from different angles. While lighting and angles can vary, deep learning models are designed to extract invariant features—such as the relative proportions of facial components—that help maintain recognition accuracy and stability.

The 128-dimensional feature vectors are systematically stored in a database, linked to each student's name and ID. This database-driven architecture facilitates swift and efficient querying, significantly enhancing both the speed and accuracy of the system. By leveraging the database for rapid retrieval and processing, the system achieves high performance and reliability, ensuring effective attendance management and face recognition operations.

The data table stores sample students information and encoded faces was captured directly from our program show in Figure 5.


Extra options

←T→			id	id_sv	encoding
Edit	Copy	Delete	11	18	-0.12459654361009598 0.13477852940559387 0.0118962...
Edit	Copy	Delete	12	18	-0.11278628557920456 0.06918761879205704 0.0109759...
Edit	Copy	Delete	13	18	-0.1549101322889328 0.05856379494071007 0.04719968...
Edit	Copy	Delete	14	18	-0.10098795592784882 0.045302875339984894 -0.01487...
Edit	Copy	Delete	15	18	-0.14864668250083923 0.11258237063884735 -0.019631...
Edit	Copy	Delete	16	18	-0.1386277973651886 0.061107978224754333 -0.005142...
Edit	Copy	Delete	24	20	-0.15934161841869354 0.1069653183221817 -0.0103026...
Edit	Copy	Delete	25	20	-0.14827485382556915 0.12114323675632477 0.0417110...
Edit	Copy	Delete	26	20	-0.167432501912117 0.17106255888938904 0.026528496...
Edit	Copy	Delete	27	20	-0.11283144354820251 0.11689244210720062 0.0156438...
Edit	Copy	Delete	28	21	-0.0174343790858984 0.09520713984966278 0.03948315...
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Figure 5. The data table stores student information and encoded faces.

3.3. Face Recognition

Student identification from the database is achieved using the Learning Similarity method [21-22]. This approach evaluates the distance between the feature vectors of two encoded images. If the images belong to the same individual, the distance between their feature vectors is minimal. On the other hand, images representing different individuals exhibit significantly larger distances, ensuring reliable differentiation and identification.

$$\begin{cases} d(img_1, img_2) \le \tau \rightarrow Same \\ d(img_1, img_2) > \tau \rightarrow Different \end{cases} \quad (1)$$

$$\begin{cases} d\left(img_1, img_2\right) \le \tau \rightarrow Same \\ d\left(img_1, img_2\right) > \tau \rightarrow Different \end{cases} \quad (1)$$

Figure 6 provides a visual representation. Instead of predicting a probability distribution to assign the most appropriate label to the input image, the algorithm measures the distance between the input image (on the right) and all images stored in the database (on the left). A predefined threshold determines whether the input image is considered similar to or different from the database images. For example, if the threshold is set at 0.5, and the distance between the input image and the middle image on the left is less than 0.5, the middle image is identified as belonging to the same individual as the input image (see Figure 6).

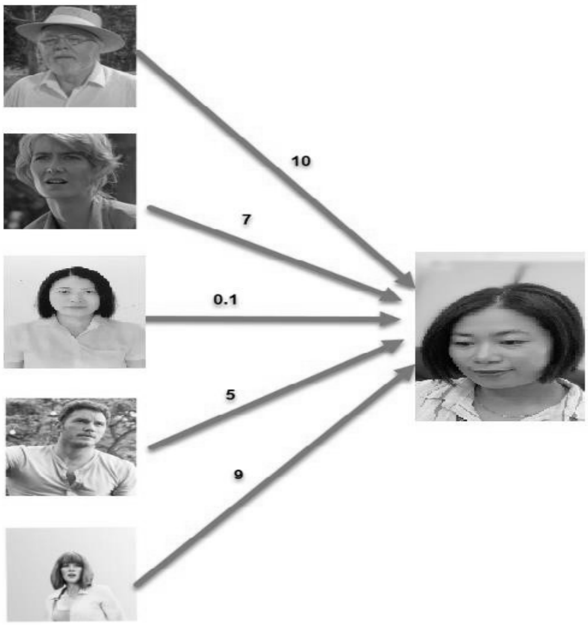


Figure 6. Illustration of similarity distance by learning similarity method

The Learning Similarity method can identify multiple images as similar to the input image, depending on the threshold value. Moreover, this method is independent of the number of classes, allowing new classes to be added without requiring retraining, making it a flexible and scalable solution.

3.4. Attendance Update

After the face recognition process, identified students are marked as present, while those not recognized are recorded as absent. This attendance data is promptly updated in the database, ensuring accurate records for academic management. The system also enables the generation of detailed daily and monthly attendance reports and supports data export to Excel files, streamlining administrative tasks and enhancing management efficiency.

4. SETTING UP AN ATTENDANCE SYSTEM

The attendance system is implemented on the Windows 10 operating system using the Python programming language. It utilizes a range of powerful libraries, including OpenCV, TensorFlow, dlib, and face_recognition, to ensure robust functionality and performance.

The system features a user-friendly interface, allowing users to easily manage key operations such as student management, faculty management, course management, and attendance tracking. Students are required to complete a registration form, providing all necessary information. Administrative personnel oversee the process by updating student information and uploading photographs. The system then processes and stores the students' facial data in a centralized database for seamless future use.

The main interface of the our student attendance system shows in Figure 7.

Figure 7: The interface of the our student attendance system

To evaluate the proposed model, the authors gathered experimental facial image data from 100 students enrolled in the IT K21 and IT K22 classes at the Faculty of Information Technology, Hai Phong University. For each student, 10 to 15 images were collected. These images were subsequently encoded and analyzed to extract features, which were stored in a database alongside the students' names and corresponding identification number.

4.1 Face Detection with MTCNN

The MTCNN efficiently detects

faces with exceptional accuracy, achieving a confidence level of 0.9989. It draws rectangular bounding boxes around detected faces and identifies the coordinates of five key facial landmarks: the two eyes, the nose, and the two corners of the mouth, as illustrated in the accompanying image:

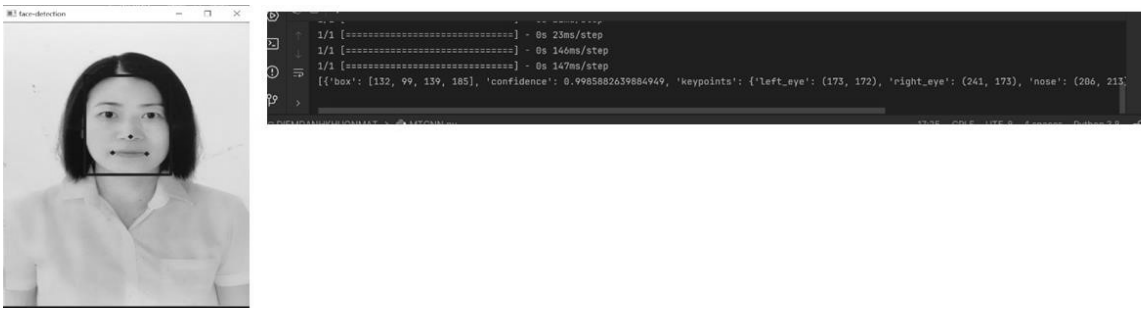


Figure 8. Face Detection with MTCNN

4.2. Student Attendance Interface

During the attendance process, students stand in front of a camera, where the system employs facial recognition technology to detect and identify them. Once identified, the system automatically records their attendance, ensuring a seamless and efficient process. The attendance results was captured from the program is show in Figure 9.

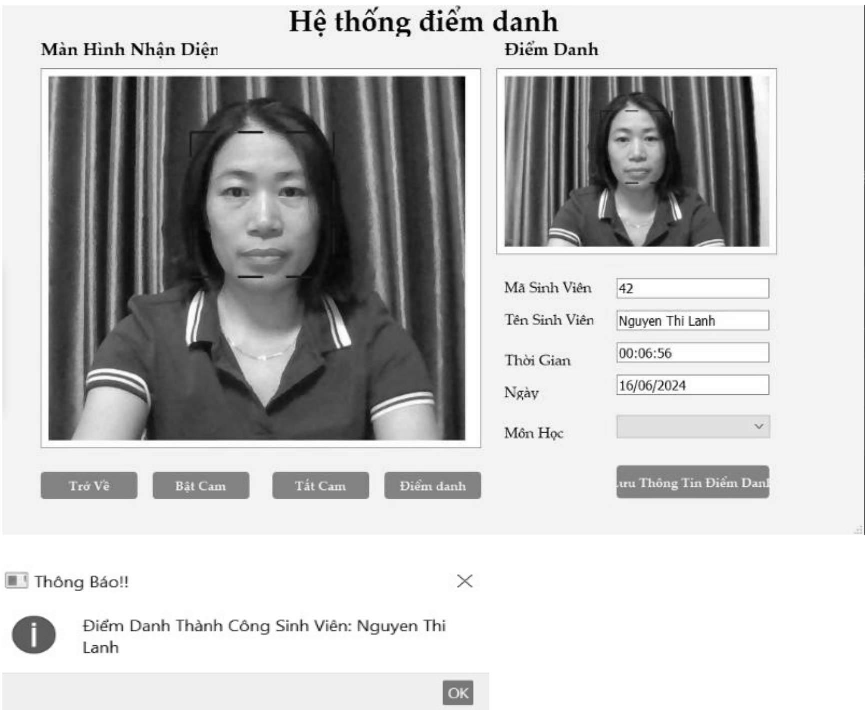
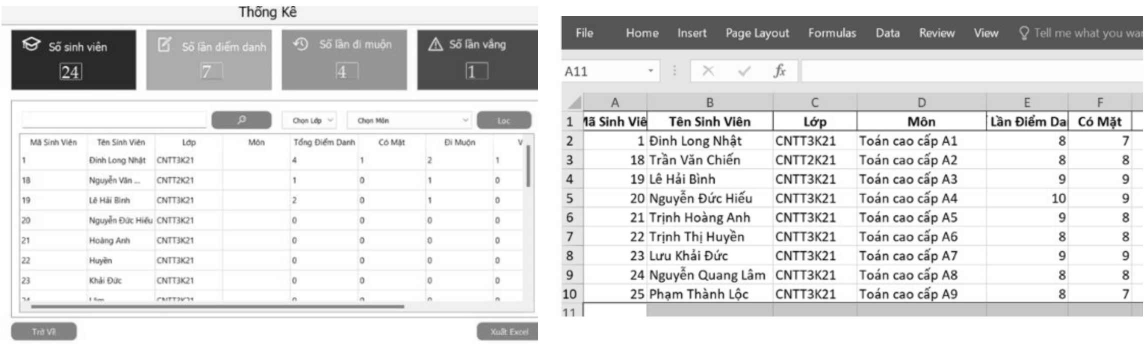


Figure 9. Attendance results

4.4 Attendance Data Statistics

The program includes a robust feature for generating detailed attendance statistics by course, along with tracking late students. This statistical data can be easily exported to Excel files, enabling streamlined management and effective monitoring of attendance records.

The experimental results demonstrate that the system can effectively and accurately detect and record student attendance in class. Implementing the model with a camera system installed at the stairways of the C3 building in the Faculty of Information Technology or within classrooms would enable automated attendance tracking. This approach ensures direct and objective monitoring of student attendance while significantly reducing the time required by lecturers. Additionally, the Faculty of Information Technology can swiftly assess the attendance patterns of individual students, facilitating timely adjustments and contributing to improved student management and overall educational quality. The attendance data statistics and data export was captured from the program is show in Figure 10.



Mã Sinh Viê	Tên Sinh Viên	Lớp	Môn	Lần Điểm Da	Có Mặt
1	Đinh Long Nhật	CNTT3K21	Toán cao cấp A1	8	7
18	Trần Văn Chiến	CNTT2K21	Toán cao cấp A2	8	8
19	Lê Hải Bình	CNTT3K21	Toán cao cấp A3	9	9
20	Nguyễn Đức Hiếu	CNTT3K21	Toán cao cấp A4	10	9
21	Trịnh Hoàng Anh	CNTT3K21	Toán cao cấp A5	9	8
22	Trịnh Thị Huyền	CNTT3K21	Toán cao cấp A6	8	8
23	Lưu Khải Đức	CNTT3K21	Toán cao cấp A7	9	9
24	Nguyễn Quang Lâm	CNTT3K21	Toán cao cấp A8	8	8
25	Phạm Thành Lộc	CNTT3K21	Toán cao cấp A9	8	7

Figure 10. Attendance data statistics and data export

5. CONCLUSION

This paper proposes the development of a student attendance system that integrates real-time face detection and recognition using the Multi-task Cascaded Convolutional Neural Networks (MTCNN) model. The system achieves a relatively high level of accuracy, particularly with frontal, high-quality images. It provides significant support for educators by streamlining the management and monitoring of students' learning and progress. Key features include displaying student facial images, accessing searchable student information, updating and editing student records, and exporting essential data in multiple formats.

The advantages of the system compared to some published studies include using the MySQL database system for data storage. This allows for a very large face storage capacity, fast retrieval speed, and high accuracy. When a new face needs to be added, the system updates it directly without requiring retraining of the data from scratch, saving a significant amount of time in preparing training data.

Despite its advantages, the system has certain limitations. It struggles with images of students wearing glasses, taken from angled perspectives, or captured in low-light conditions, which can result in longer processing times or failures in face recognition. Future research should aim to integrate advanced deep learning models to improve accuracy and reliability, addressing these challenges and enhancing overall system performance.

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