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AUTOMATED STUDENT ATTENDANCE MONITORING SYSTEM IN CLASSROOM BASED ON CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Attending classes by students is associated with the assimilation of educational material by students and the ability to plan and organize activities. However, at present in educational institutions, as a rule, student attendance is recorded manually. Activities are performed frequently and repeatedly, thus wasting instructors' study time. Additionally, the face is one of the most widely used biometric characteristics for personal identification so an automated attendance system using face recognition has been proposed. In recent years, convolutional neural networks (CNN) have become the dominant deep le11arning method for face recognition. In this article, the features of building an automated student attendance system by biometric face recognition using the convolution neural network model has been discussed. Analyzed and solved the main tasks that arise when building an automated student attendance monitoring system: creating a dataset of students' face images; building and training a biometric face recognition model; face recognition from the camera and registration in the database; extension to the face image dataset. The use of the capabilities of the Python and OpenCV libraries is shown. The conducted testing of the accuracy of the developed CNN model of biometric face recognition showed good results – the overall accuracy score is not less than 0.75. The developed automated student attendance monitoring system in classrooms can be used to determine student attendance in different forms of the educational process. Its implementation will significantly reduce the monitoring time and reduce the number of errors in maintaining attendance logs. The introduction of an automated attendance monitoring system will significantly improve the organization of the educational process to ensure its quality.

Keywords: Biometric Face Recognition; Convolutional Neural Network; Deep Learning; Computer Vision; Face Detection; Haar Cascade; Image Processing; Face Dataset

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INTRODUCTION

Academic attendance is an important component of the organization of the educational process. Student attendance, which means the presence of students in the classroom in order to master the educational program, is associated with the assimilation of educational material by students and the ability to plan and organize activities. Those, the class attendance determines the academic performance and organization of students, makes it possible to predict the quality of training of future specialists and manage the course of the educational process in an educational institution. It should be noted that the organization of the student attendance monitoring system in educational institutions allows us to assess the number of absenteeism, as a characteristic of not only the activity of students, but also the demand for the discipline, its relevance and develop measures to improve the organization of the educational process. The collection, analysis and systematization of data on student attendance usually take into account information from the attendance registers in classrooms. Such journals are filled in either by teachers or by responsible students manually. Therefore, the step of collecting attendance data is lengthy and usually not particularly objective.

LITERATURE REVIEW

Faces are one of the most widely used biometric characteristics for personal identification. The first works in this direction began to appear in the 1990s, but since that time significant progress has been made in the field of face detection and recognition [1]. Face recognition (FR) is defined as the process of

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identifying people using a face image [2–7]. Face recognition is widely used in biometrics, when organizing security, accessing controlled areas, monitoring compliance with the law by various law enforcement agencies [8–9]. At present, the problem of effective face recognition is a priority in the list of research papers on computer vision. One of the most effective approach to its solution is the development and application of new neural network models [10–11], especially based on deep learning [9]. In recent years, as analysis of the literature shows, convolutional neural networks (CNN) have become the dominant deep learning method for recognizing visual objects [12–14]. This is due to several advantages of convolutional neural networks - invariance to scale, translation, rotation, and lighting. The analysis showed that CNNs are able to solve various practical problems where face recognition is required [15]. In addition, the disadvantage of CNN – long training time, can be eliminated by using pretrained CNNs and the possibility of additional training by increasing variations in the dataset and increasing the size of the dataset [16]. It should be noted that the accuracy of CNN recognition strongly depends on the size of the training datasets [17]. But for face recognition, there is a large training data set – ImageNet [18], which contains more than 14 million images, which makes it possible to make effective preliminary training of CNN [19]. Complex datasets are also used for deep convolutional neural networks (DCNNs), for example, WIDER FACE [20–21] and MegaFace Challenge [22], Labeled Faces in the Wild (LFW) [23]. Another advantage of CNN is the ability to implement them on powerful GPUs [24] and improvements in the CNN architecture [25]. Accuracy analysis of biometric face recognition was performed for different DCNN models (CenterFace [26], SphereFace [27], FaceNet [28], CosFace [29], ArcFAce (LResNet100E-IR) [30]) when using different sets (MegaFace Challenge and LFW) for training (*Table* 1). Note that the MegaFace Challenge sets and their subsets (subsets - CASIA-WebFace, CACD Celerity + and Refined MS-Celeb-1M, VGG2) and LFW (FaceNet) are large-scale public databases and allow training and benchmarking to fairly compare algorithms no bias in using private datasets. This solves the problem of insufficient reproducibility of results [30] caused by the use of private databases for training with modern CNN methods [31]. As can be seen from the analysis in the *Table* 1, the accuracy of face recognition on different DCNN models does not exceed 84 % in testing mode/

Another fact in favor of using DCNN is the simplicity of implementation, since for the implementation of face recognition systems using DCNN, the Python programming language has proven itself as one of the best for the development of artificial intelligence (AI) [32]. The language Python has many libraries that support AI. For example, the open source TensorFlow library, created by the Google Brain research team, is written using Python [33–36]. Google uses this library to program and train neural networks to learn AI. Another well-known library scikit-learn [37], which is used in AI research, for training machine learning, for controlling industrial systems.

Table 1. **Results of biometric face recognition for lfw and the mega face challenge (mf1)**

Model/Method	**Training Dataset**	**Number of NNs**	**Loss function**	**Biometric face recognition**
CenterFace	CASIA-WebFace, CACD Celerity+	1	Center Loss	65.23 % (MF1)
SphereFace	CASIA-WebFace	1	Angular softmax	75.77 % MF1 (small protocol)
FaceNet	FaceNet	1	Harmonic triplet loss	70.49 %(large protocol)
CosFace	CASIA-WebFace	1	Large Margin Cosine	79.54% (small protocol) 84.26 % (large protocol)
ArcFAce (LResNet100E-IR)	Refined MS-Celeb-1M, VGG2	1	Additive Angular Margin loss	83.27 % (MF1)

***Source*: compiled by the author**

In general fields of application of image recognition in Python, it is possible to work with this direction through the OpenCV library [38–44]. OpenCV is an open source library containing over 2,500 image processing and video stream algorithms. The simplest actions available in OpenCV are opening images and video streams, overlaying text and other objects, applying filters to an image, and distorting. Python has several powerful and popular libraries that are designed to work with big data: analysis, visualization, trend forecasting [45–46]. For example, the Matplotlib library is one of the most popular data visualization libraries. The Pandas library is used to analyze information.

PURPOSE AND TASKS OF WORK

Within the framework of this study, it is proposed to automate the process of monitoring student attendance in classrooms using modern computer vision technologies – technologies for biometric students' faces recognition based on the DCNN model. The purpose of this article is to develop an automated student attendance monitoring system in classrooms based on the developed and previously trained DCNN, which will allow for an objective, prompt and accurate record of student attendance in classrooms.

Based on the DCNN's review and given Python library features, the structure of the automated student attendance monitoring system (AAM) is proposed, which allows solving the following (*Fig. 1*):

– Creating a dataset of face images;

– Building and training DCNN model for face recognition;

– Face recognition from the camera;

– Expanding the dataset

– Formation of attendance reports.

Consider the features of the components of the AAM system.

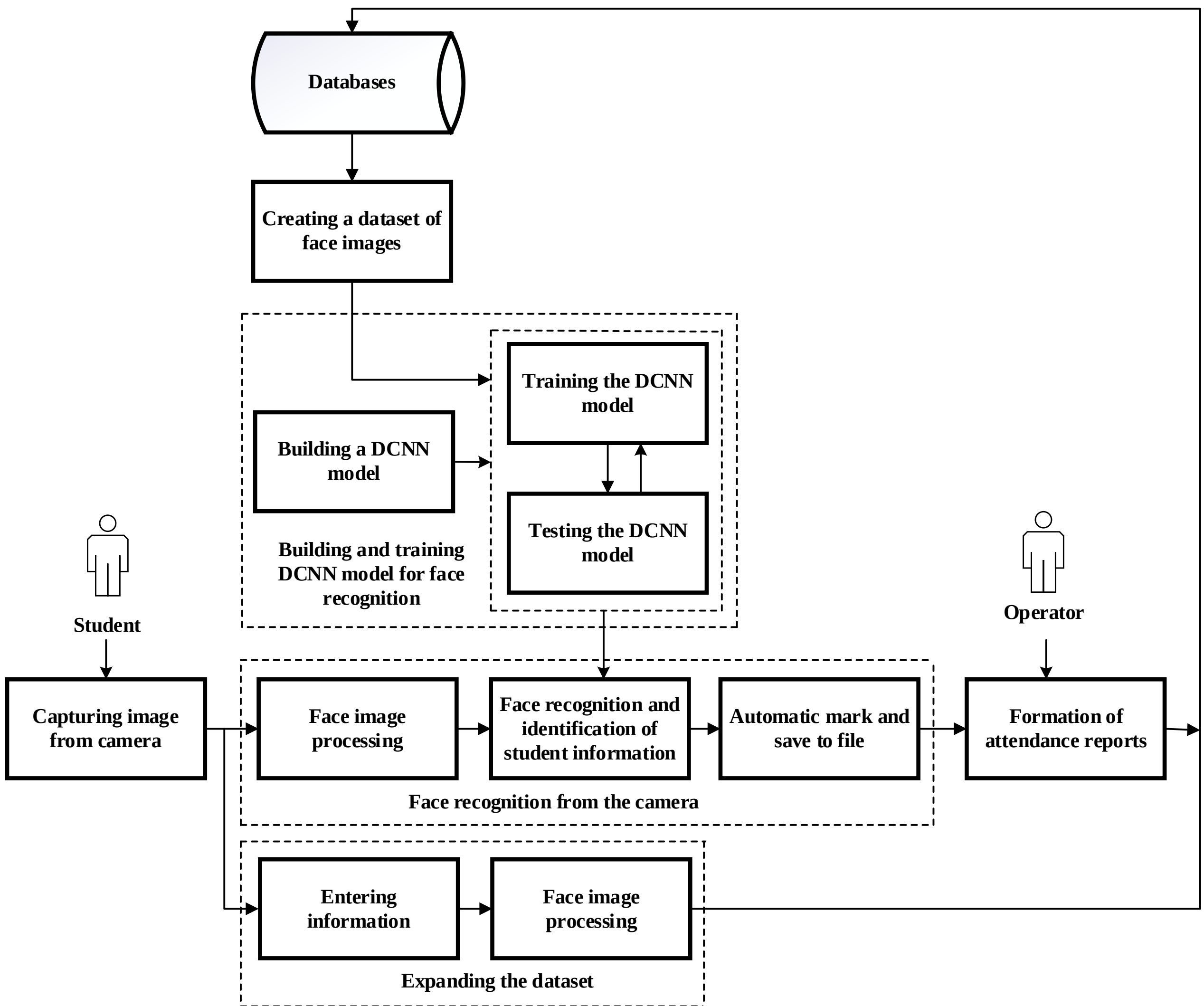

Fig. 1. **Generalized diagram of the AAM structure**
***Source*: compiled by the author**

AUTOMATED ATTENDANCE MONITORING SYSTEM

From the generalized diagram of the AAM structure (*Fig. 1*), it is clearly seen that it is necessary to create databases to store data for all components of the AAM system. Databases for the AAM system contain:

• dataset of students' faces images (original students' faces images, processed image sets for the DCNN model)

• data files, in which students' information is written (full name, ID, group, courses, ...), attendance logs in classrooms and also information of these images (file addresses, labels, ...)

The use, processing, expansion of data in the database are indicated below in AAM system.

CREATING DATASET OF STUDENTS' FACE IMAGES

To build an accurate DCNN model, you need to create a comprehensive and high-quality dataset for training it. The task of creating datasets is very important in building neural network models.

The process of creating a dataset of students' face images is shown in *Fig. 2*, and provides the following steps:

- automatic localization of faces in the image. The dataset must include image fragments that contain only the interested object – the face. For this, the object detection method based on Haar Cascade was used [42–44];
- creating a dataset of students' information. It is proposed to store data in the format of an image, student's ID, and his information. An example is shown in *Fig. 3.*
- splitting data**.** According to deep learning methodology for DCNN, 3 datasets need to be prepared – training set – 70 %, validation set –15 %, and testing set – 15 %.
- preprocessing data. Suggest the representation of all sets in the form of matrices; their normalization (range [0,1]), scaling to standard sizes –(64x64x3) or (128x128x3).

An example of a dataset of students' face images is shown below (*Fig. 3*).

BUILDING AND TRAINING A MODEL FOR FACE RECOGNITION

As shown above, a great deep learning technique for classifying images (namely face images) is to use a Deep Convolutional Neural Network (DCNN) [6; 9]. The DCNN model is defined by a sequence of layers. The developed generalized block diagram of the model using CNN is shown in *Fig. 4*. *Table 2* summarizes the developed DCNN model. The notation is used for the description, which areaccepted in Keras library notation.

Table 2. **Brief introduction of the DCNN model**

Layers	Hyper-parameter	
Input	Size of input (facial image)	64x64x3
Conv1D_1	Unit	64x64x3
	No. of filter	64
	Kernel size	3x3
	Pooling size	2x2
	Activation Function	ReLu
	Dropout	0.25
Conv1D_2	Unit	32x32x64
	No. of filter	128
	Kernel size	3x3
	Pooling size	2x2
	Activation Function	ReLu
	Dropout	0.25
Conv1D_3	Unit	16x16x128
	No. of filter	256
	Kernel size	3x3
	Pooling size	2x2
	Activation Function	ReLu
	Dropout	0.25
Flatten	Unit	8x8x256
Dense_1	Unit	3000
	Activation Function	ReLu
	Dropout	0.5
Dense_2	Unit	N_classes
	Activation Function	Softmax

***Source*: compiled by the author**

The first 3 layers are Conv2D convolutional layers. Between the Conv2D layers and the dense layer is the bonding layer "Flatten". This one serves as a link between the convolution and dense layers. Dense is a type of layer that is used in many cases for neural networks for the output layer. Thanks to the activation function for the output layer, therefore, the DCNN output can be interpreted as a probability (value between 0 and 1).

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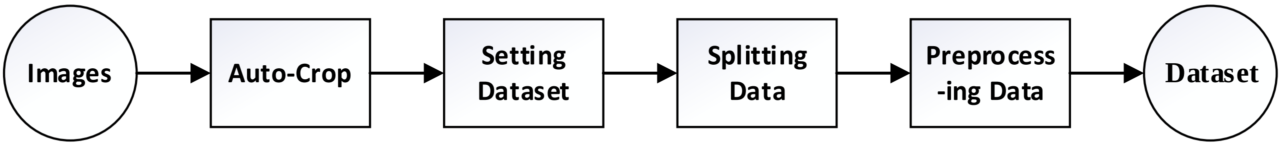

Fig. 2. **The process of creating a dataset of students' face images**
***Source*: compiled by the author**

STUDENT FACE RECOGNITION

When recognizing students' faces, the main task of the AAM is performed - automatic registration of the student. The following steps are provided *(Fig. 5):*

- Capturing image from camera
- Face image processing. Pre-processing the received images from a video camera for image recognition process faces.
- Face recognition and identification of student information (Face RegID) using developed and previously trained DCNN. The input image of the student's face is associated with the image from the trained set and its identifiers (ID student, full name).

An example of automatic student face recognition is shown in *Fig. 6*.

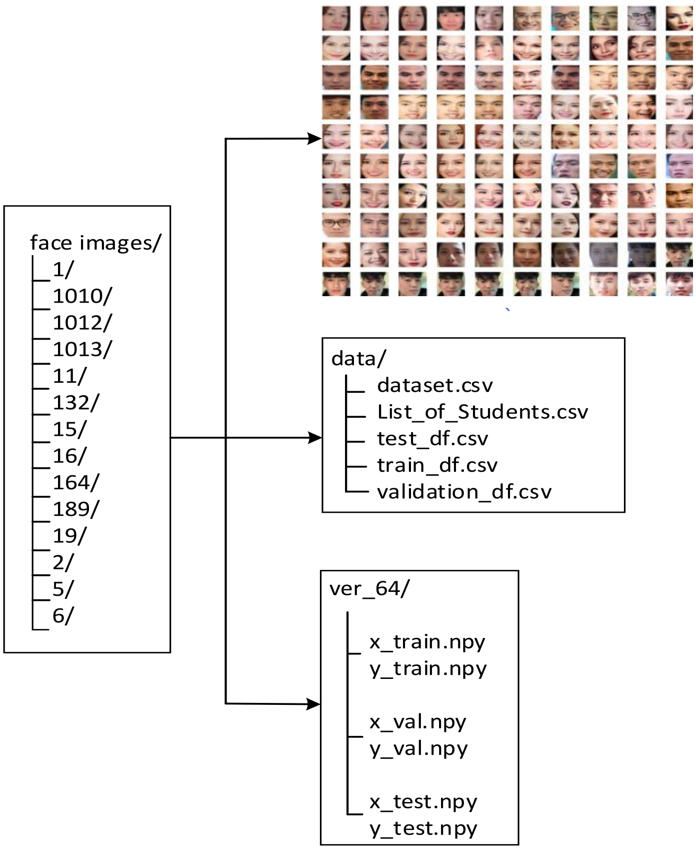

Fig. 3. **Example of a dataset of students' face images**
***Source*: compiled by the author**

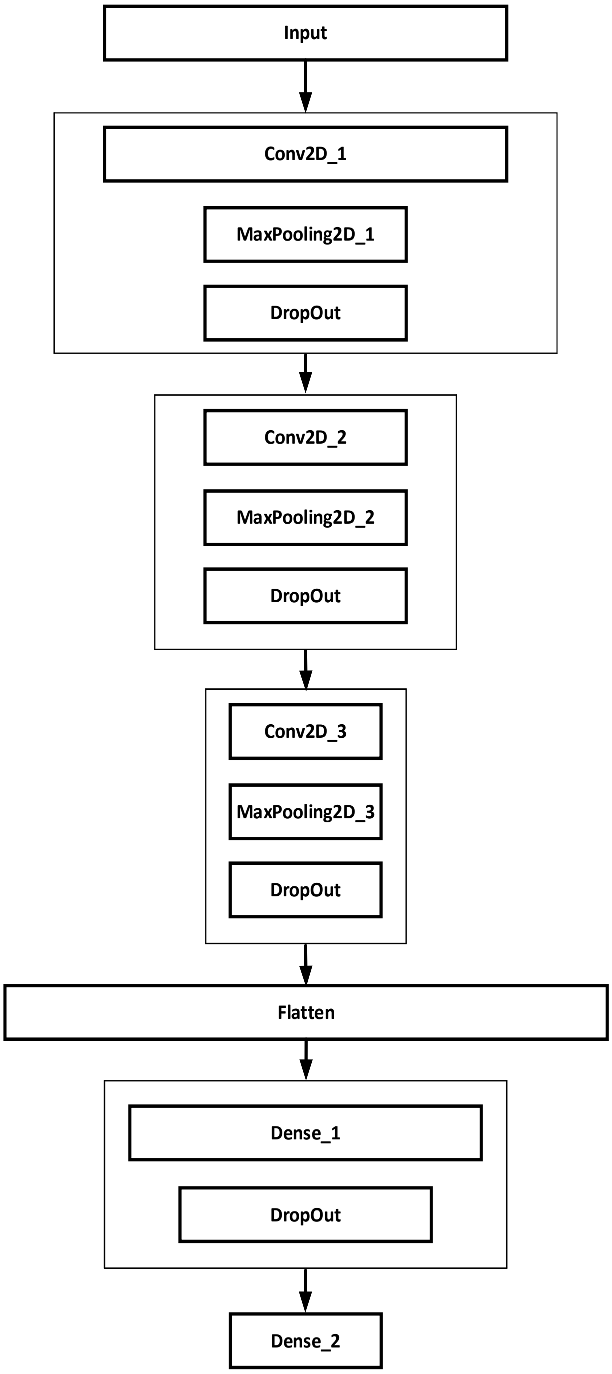

Fig. 4. **Generalized block diagram of a model using DCNN**
***Source*: compiled by the author**

EXPANDING THE DATASET

To ensure the efficient work of the DCNN model, an up-to-date volume of the database is required for network training.

To do this, it is necessary to periodically add new students' face images and also face images of new students, which is based on the following actions:

- entering the id and full name of students;
- obtaining images from the camera and performing face localization;
- adding the resulting face image to the dataset.

The resulting dataset is used to retrain the model on the extended dataset. This process is shown in *Fig. 7*. An example of adding a student's face image from a camera to the dataset is shown in *Fig. 8*.

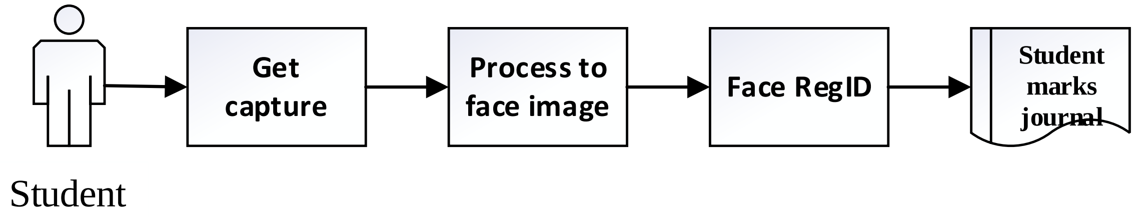

Fig. 5. **Process diagram of student face recognition**
***Source*: compiled by the author**

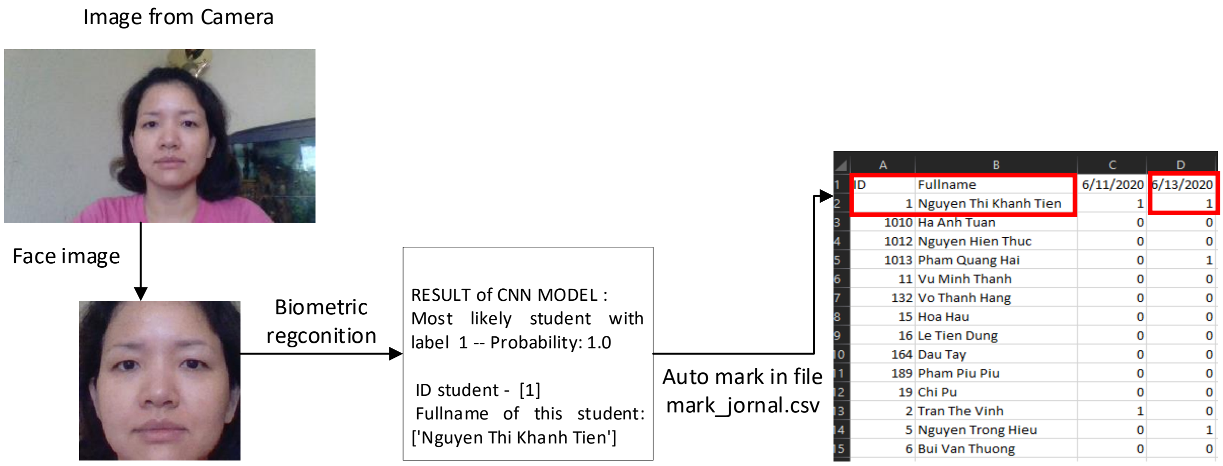

Fig. 6. **Example of performing automatic student face recognition**
***Source*: compiled by the author**

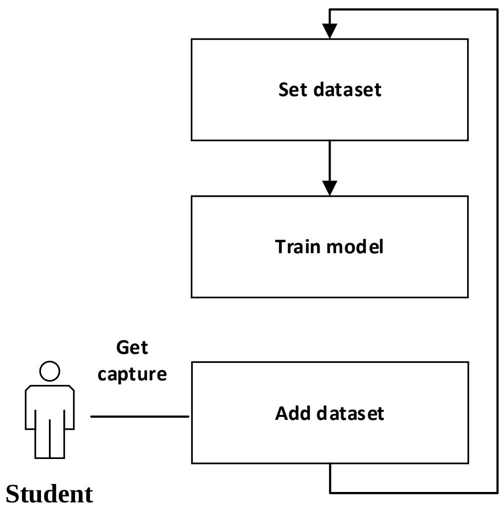

Fig. 7. **Process of expanding the dataset to retrain the model**
***Source*: compiled by the author**

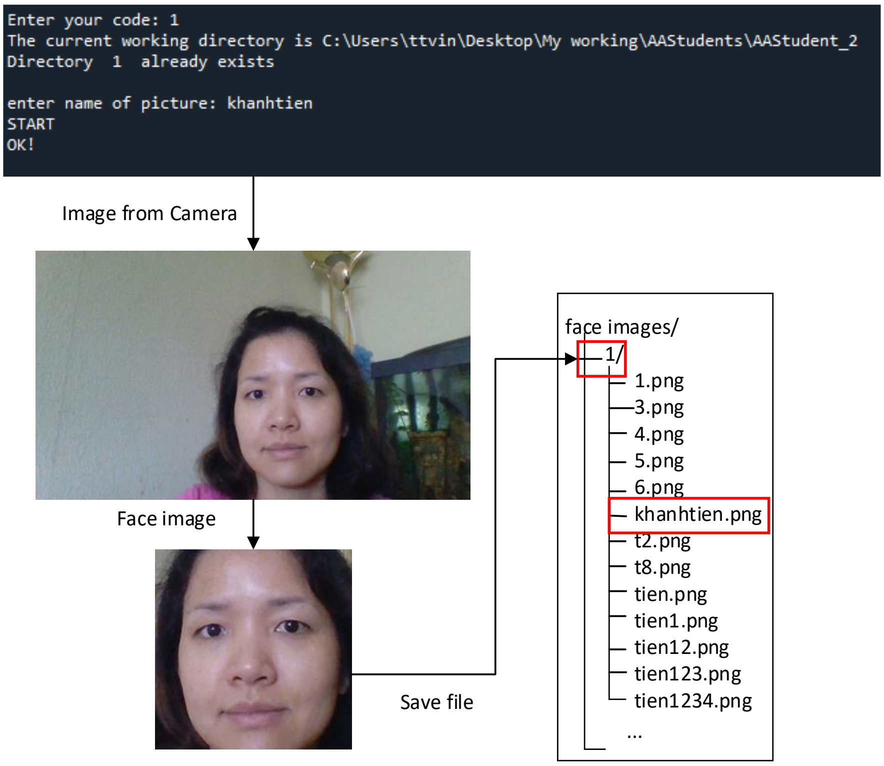

Fig. 8. **An example of adding a student's face image from a camera to the dataset**

***Source*: compiled by the author**

EXPERIMENTAL CHECK OF THE AAM SYSTEM PERFORMANCE

Testing of the developed AAM system was carried out in real conditions on 16 subjects. When testing the recognition accuracy based on the DCNN model, the following characteristics were calculated: The precision, The recall, F1-score for each class (example in *Table* 3) [47]. The evaluation diagram of the developed DCNN model, which was tested in real conditions, and were obtained after 2500 iterations, is shown in Fig. 9.

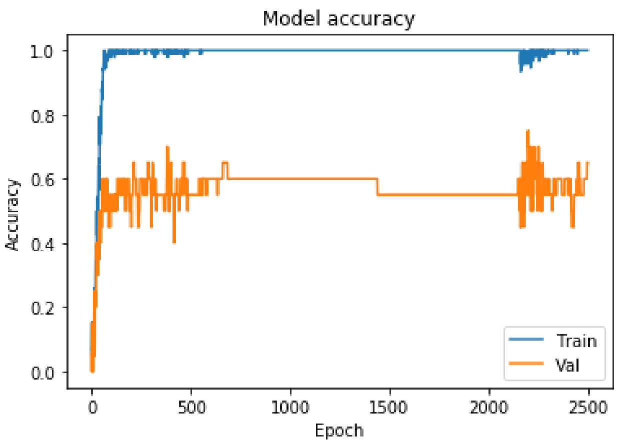

Fig. 9. **Diagram of the average accuracy of the CNN model during training (after 2500 iterations) for training and validation sets**

***Source*: compiled by the author**

Table 3. **Evaluating the accuracy of the biometric facial recognition DCNN model for set validation**

Accuracy Score of each class			
Class	Precision	Recall	F1-score
2	0	0	0
3	1.00	0.50	0.67
4	0	0	0
5	0	0	0
7	0.5	1.00	0.67
8	0	0	0
9	1.00	1.00	1.00
10	1.00	1.00	1.00
11	1.00	1.00	1.00
12	0	0	0
13	0.5	1.00	0.67
14	1.00	1.00	1.00
15	1.00	1.00	1.00
16	1.00	1.00	1.00
Accuracy			0.75

***Source*: compiled by the author**

The maximum average accuracy estimate for the training set is 1, for the validation set it is 0.75. This recognition accuracy is satisfactory since the system provides for error correction when entering the attendance record data. In the future, it is planned to test AMP on a larger number of students and to refine the error correction subsystem.

CONCLUSION

The article discusses the features of building a automated student attendance monitoring system using the DCNN neural network model for biometric face recognition. For this, the capabilities of the Python and OpenCV libraries are used. The accuracy of this CNN model was tested for each class (*Table 3*) and the average accuracy of the model in the learning process (*Fig. 9*). Accuracy measure, recall measure, F1-score are used to evaluate the accuracy of each class of the DCNN biometric face recognition model, the result is shown in *Table 3* with an overall accuracy score of 0.88. During training, after 2500 iterations, the maximum average accuracy estimate for the training set is 1, for the validation set – 0.75. To ensure the functioning of the AAM system, data on students must be continuously expanded.

The developed automated student attendance monitoring system in classrooms can be used to determine student attendance, student exams in various forms of the educational process. Its implementation will significantly reduce the monitoring time and errors in maintaining attendance logs. The introduction of the AAM system will significantly improve the organization of the educational process to ensure its quality.

The research was carried out within the framework of a cooperation agreement between Ho Chi Minh City University of Transport and Odessa National Polytechnic University on the basis of the Ukrainian-Vietnamese Cooperation Center. It is planned to introduce the AAM system at the Ho Chi Minh City Transport University.

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АВТОМАТИЗОВАНИЙ МОНІТОРИНГ ВІДВІДУВАННОСТІ СТУДЕНТАМИ НАВЧАЛЬНИХ ЗАНЯТЬ НА ОСНОВІ ЗГОРТОЧНИХ НЕЙРОННИХ МЕРЕЖ

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АНОТАЦІЯ

Відвідування занять студентами пов'язане з засвоєнням навчального матеріалу студентами та вмінням планувати і організовувати діяльність. Однак в даний час в освітніх закладах, як правило, облік відвідування студентів проводиться в ручну. Заходи виконуються часто і багаторазово, і таким чином, витрачають навчальний час викладачів. Крім того, обличчя є однією з найбільш широко використовуваних біометричних характеристик для ідентифікації особистості, тому була запропонована автоматизована система відвідуваності з використанням розпізнавання облич. В останні роки згорткові нейронні мережі стали домінуючим методом глибокого навчання для розпізнавання осіб. У цій статті розглянуті особливості побудови системи автоматизованого обліку відвідуваності студентами шляхом біометричного розпізнавання облич з використанням згорточної нейромережевої моделі. Проаналізовано та вирішені основні задачі, які виникають при побудові автоматизованого моніторингу відвідуваності студентам навчальних занять: створення набору даних, зображень облич студентів; побудова і навчання моделі для біометричного розпізнавання особи; розпізнавання особи з камери і реєстрація в базі даних; розширення набору даних зображень облич. Показано використання можливостей бібліотек Пітон і OpenCV. Проведене тестування точності розробленої згорточної нейромережевої моделі для біометричного розпізнавання осіб показало хороші результати – загальна оцінка точності не менше 0.75. Розроблена система автоматизованого моніторингу відвідуваності учнями навчальних занять може бути використана для визначення відвідуваності учнями при різних формах освітнього процесу. Її впровадження дозволить істотно скоротити час моніторингу і зменшити кількість помилок при веденні журналів відвідуваності. Впровадження системи автоматизованого моніторингу відвідуваності значно поліпшить організацію освітнього процесу щодо забезпечення його якості.

Ключові слова: біометричне розпізнавання осіб; згорточна нейронна мережа; глибоке навчання; комп'ютерний зір; каскад Хаара; обробка зображень

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АВТОМАТИЗИРОВАННЫЙ МОНИТОРИНГ ПОСЕЩАЕМОСТИ СТУДЕНТАМИ УЧЕБНЫХ ЗАНЯТИЙ НА ОСНОВЕ СВЕРТОЧНОЙ НЕЙРОННЫХ СЕТЕЙ

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АННОТАЦИЯ

Посещение занятий студентами связано с усвоением учебного материала студентами и умением планировать и организовывать деятельность. Однако в настоящее время в образовательных заведениях , как правило, учет посещения студентов проводится в ручную. Мероприятия выполняются часто и многократно, таким образом, тратят учебное время преподавателей. Кроме того, лицо является одной из наиболее широко используемых биометрических характеристик для идентификации личности, поэтому была предложена автоматизированная система посещаемости с использованием распознавания лиц. В последние годы сверточные нейронные сети стали доминирующим методом глубокого обучения для распознавания лиц. В статье рассмотрены особенности построения системы автоматизированного учета посещаемости студентами путем биометрического распознавании лиц с использованием сверточной нейросетевой модели. Проанализированы и решены основные задачи, которые возникают при построении автоматизированного мониторинга посещаемости учащимися учебных занятий: создание набора данных, изображений лиц студентов; построение и обучения модели для биометрического распознавания лица; распознавание лица с камеры и регистрация в базе данных; расширение набора данных изображений лиц. Показано использование возможностей библиотек Питон и OpenCV. Проведенное тестирование точности разработанной сверточной нейросетевой модели для биометрического распознавания лиц показало хорошие результаты – общая оценка точности не менее 0.75. Разработанная система автоматизированного мониторинга посещаемости учащимися учебных занятий может быть использована для определения посещаемости учащимися при разных формах образовательного процесса. Ее внедрение позволит существенно сократить время мониторинга и уменьшить количество ошибок при ведении журналов посещаемости. Внедрение системы автоматизированного мониторинга посещаемости значительно улучшит организацию образовательного процесса по обеспечению его качества.

Ключевые слова: биометрическое распознавание лиц; свёрточная нейронная сеть; глубокое обучение; компьютерное зрение; каскад Хаара; обработка изображений

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