Implementing CNN-Based Facial Recognition in Education: Privacy, Bias Mitigation, and Technological Advancements

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Abstracts

The Study explores the integration of Convolutional Neural Networks (CNN)-based facial recognition into student management systems, emphasizing its potential and associated ethical challenges. The proposed system automates attendance tracking, access control, and student identity verification, employing AdaBoost for enhanced classification accuracy and CNNs for high-precision image recognition. The methodology involves three steps: pre-processing using Gaussian Log filters to reduce noise and improve image quality; face detection with the Viola-Jones algorithm; and HRPSM_CNN for feature extraction and classification. The datasets utilized AR and FERET—comprise facial images with varying conditions, such as occlusions and lighting variations, ensuring robustness in evaluation. Training and testing split images in an 80:20 ratio, and the results are analyzed based on error and misclassification rates. Key findings highlight that the system achieves a 95% accuracy in recognizing occluded faces with reduced computational time. However, the research underscores the importance of addressing data privacy concerns and algorithmic biases. The proposed HRPSM_CNN method outperformed traditional models by effectively handling noise and unconstrained environments, offering a reliable solution for real-time applications in educational settings. The study concludes with recommendations for ethical integration, emphasizing transparency, fairness, and robust data security measures to ensure responsible deployment in diverse educational environments. The findings contribute to the growing discourse on leveraging AI for administrative efficiency while maintaining ethical integrity.

Keywords: CNN-based facial recognition, Student management systems, Ethical considerations, Bias mitigation, Transparency

1. INTRODUCTION

Recognition of facial emotions using generic CNN architecture. Preprocessing predefines the input layer to a specific size, allowing it to be inserted into the following layer(He, 2020). To recognize faces in each picture, the project employed OpenCV, a prominent computer vision toolkit with pre-trained filters. In addition, the project use Adaboost to detect and crop faces. This step drastically reduces the size. The input layer is then transmitted to the Convolution2D layer, where the number of filters is controlled by a super-parameter. A collection of filters, such as the kernel, is made up of randomly generated weights(Abdelbar et al., 2024). Each filter, such as a sliding window, scans the whole picture to create a feature graph with shared weights. The convolution layer creates a feature map that depicts how pixel values are increased for edge, light, and pattern detection. Pooling to minimize the dimension behind the convolution layer is a reasonably significant step in developing a generic CNN architecture, since adding additional convolution layers might raise computing costs. The project employs the MaxPooling2D method, a prominent pooling approach that use a 2x2 window to explore feature maps, preserving only the highest value of pixels. When pixels are combined, the picture size is decreased by four. The project's output layer employs softmax as the activation function rather than sigmoid. The layer returns the probability for each facial expression class. In this method, the CNN model can calculate the likelihood of each emotion and choose the emotion with the greatest predictive score as the recognition result. Figure 8 depicts the CNN architecture that was eventually created to detect faces and identify unique facial expressions for each one(Chai et al., 2021).

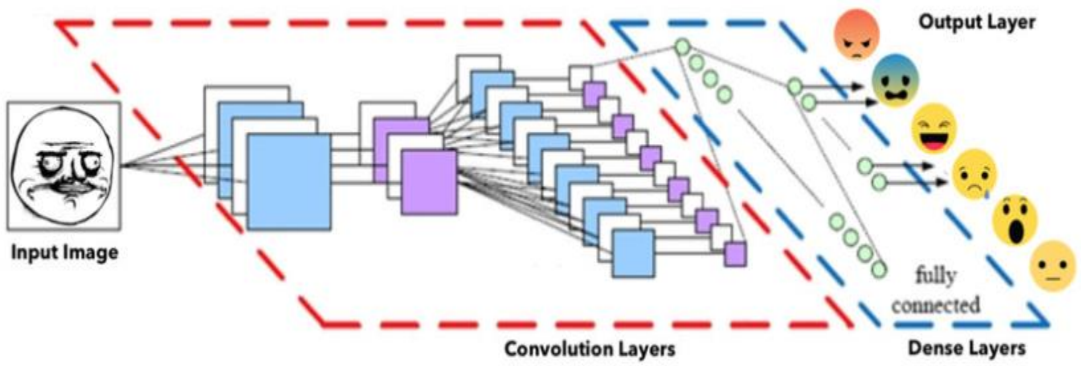


Fig.1 CNN Architecture for Facial Emotion Recognition: From Input Image to Emotion Classification
Source: (Tang et al., 2019)

Nevertheless, there are difficulties and moral dilemmas associated with this integration process. As face recognition technology becomes more commonplace, worries about algorithmic bias, data security, privacy invasion, and individual rights have grown(Almeida et al., 2022). These worries are exacerbated in the case of student management systems by the delicate nature of the data involved and the possible effects on students' autonomy and privacy rights. Furthermore, the accuracy and dependability of face recognition algorithms present serious technical challenges that need to be resolved for successful deployment, especially in the varied and dynamic surroundings characteristic of educational settings(Dhirani et al., 2023).

The purpose of this essay is to examine the moral and technical ambiguities that arise when CNN-based face recognition is included into student management systems. We want to provide a framework that tackles these issues and makes it easier for educational institutions to use face recognition technology responsibly by looking at the relationship between ethics, technology, and education(Chowdhury et al., 2020). We work to close these gaps and clear the path for the moral and successful integration of facial recognition technology into student management systems by using a multifaceted strategy that includes ethical principles, technical developments, and stakeholder interaction(Potdar et al., 2022). Facial recognition technology must be included into a student management system using a methodical process that involves many phases. In order to create an extensive database, data collecting first entails obtaining and analyzing pictures of students' faces. Accurate face recognition is then ensured by model training using Convolutional Neural Networks (CNNs)(C. R. Kumar et al., 2023). By improving decision-making procedures, especially for difficult cases, AdaBoost further improves the model's accuracy. In order to implement features like automatic attendance and safe access control, the trained model must be integrated into the student management system for real-time face recognition(Lu et al., 2021).

Nonetheless, there are a number of issues and concerns with this integration process. Concerns about security and privacy need adherence to ethical standards and privacy regulations in order to protect student data from unwanted access(Zhao, 2023). For face recognition algorithms to minimize false positives and negatives and to promote fairness, accuracy and bias mitigation are essential. Furthermore, sufficient infrastructure and hardware are needed to enable the system's features in educational settings. Addressing these issues and promoting the moral and efficient use of face recognition technology into student management systems are the goals of the research objectives listed(Coskun et al., 2017). The research aims to shed light on the effectiveness, efficiency, and security of such systems by examining existing student management procedures, creating a prototype of an IT-based Student Management System (SMS) using face recognition, and assessing the advantages and disadvantages of the system. The project is to help close the gaps in CNN-based face recognition for student management systems while guaranteeing ethical standards and practical implementation via thorough testing of facial recognition, fingerprint identification, and data security transfer(Prasetyo et al., 2021).

Need for the Study

The paper addresses the need for an advanced facial recognition-based student management system. The integration of AI, specifically CNNs and AdaBoost, offers solutions to challenges in educational administration, such as attendance tracking, access control, and identity verification. Traditional manual methods are prone to inefficiency and human error, necessitating automated systems to improve accuracy, security, and administrative efficiency. The study explores how facial recognition, a promising tool in smart campus initiatives, can transform educational management by enhancing operational efficiency and preventing issues like attendance fraud. However, implementing such systems is fraught with challenges, including privacy concerns, data security, algorithmic bias, and the sensitivity of student data. Ensuring accuracy and fairness in diverse educational environments remains a technological hurdle.

The need for this study arises from the gap between the potential of facial recognition technology and its practical, ethical deployment in schools. By identifying these challenges and offering a comprehensive framework, the research aims to bridge the gap between technology and ethical standards. This includes addressing bias, improving algorithm accuracy, and ensuring compliance with data protection laws. Ultimately, the research seeks to design and test a prototype system that demonstrates the feasibility and benefits of an IT-based student management solution, ensuring it aligns with institutional goals and ethical practices.

2. LITRATURE REVIEW

In the weighted score fusion scheme, the weights have to be set physically. It is very tough to find the optimized weight since the results are varying abruptly when the weights are different. Hence there is a need for setting different weights constantly by experiments to calculate the optimal weights. Authors Y. Zhang et al. (2019) developed a fusion based model to calculate the optimized weight where they are applying fusion multiplication for sparse representations(Y. Zhang et al., 2019). The proposed fusion model for easy use and not necessary to provide artificial set weights(J. Li et al., 2022). But the reliability must be maintained between correlation and classification error for experiment analysis. In general, face recognition is considered as Two Step Face Recognition (TSFR) where the original facial image is compared with the training samples to recognize the face in an accurate manner. The Figure 2. depicts the various steps that are followed in face recognition that helps to detect and align the face. Initially, the face is localized by using the facial detector then preceded with that detected face is aligned with coordinates of canonical and finally the face recognition system is implemented. The anti-spoofing technique found the actual face that helps to process the images for handling various situations.

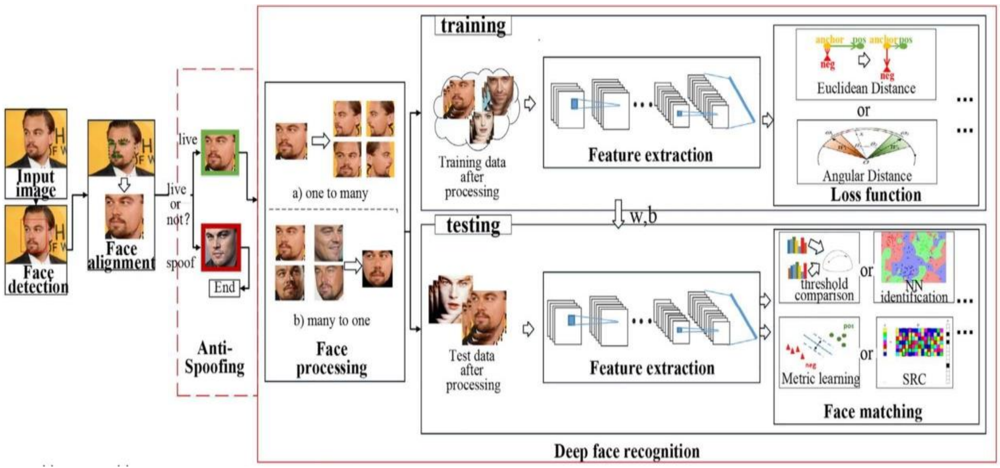


Figure 2 Different steps in Face recognition
Source:(M. Wang & Deng, 2021)

H.Zhang et al. (2019) comes across the problem of identifying the heterogeneous images from the wild that are captured over unconstrained environments as either by frame or video. Hence they developed a unique model as Set-to-Set (S2S) distance measure to calculate the similar properties among two sets of images in order to achieve the objective of attaining maximum accuracy for unrestrained images that are affected by various illumination and posture variations. In this S2S, it adjusts with the KNN average pooling to calculate similar points that are computed over the media as two sets which makes the facial identification less vulnerable to the deprived representation compared to the conventional feature average pooling. In addition to that, other metrics are also combined into the proposed S2S distance framework that includes predefined and previously learned ones to obtain better results(H. Zhang et al., 2020). They utilized IJB-A face data set for experimental analysis to prove that the proposed method showed better accuracy and also being a baseline for other existing algorithms. Generally, in any face recognition system, it is a very complex process to extract features for a conventional facial expression recognition system. Hence a facial recognition model based on convolutional neural networks to detect edges is introduced by **H.Zhang et al. (2019)** initially, the normalization is done for facial images and also the edges of every layer are extracted with the convolution process. The extracted information is protected by superimposing over every feature image that in turn secures the texture image information. Then, the size reduction is done by the maximum pooling method(H. Zhang et al., 2020). At last, the softmax layer is functioning to recognize and classify the test sample expression. To check the sturdiness of the proposed method, it is analysed with Fer-2013 and LFW data sets. The proposed method ensures 88.56% accuracy for a set of iterations with the training speed of 1.5 greater than the conventional algorithm. In order to incorporate the practical face recognition systems, **J.Y.Choi et al. (2020)** proposed efficient facial representation methods. Most of the DCNN - based FR systems employ the grey scale or primary color images with input representations for DCNN architectures. They planned to implement Gabor face representation over DCNN architecture to improve face recognition performance. Hence, they introduced a unique "Gabor DCNN (GDCNN) ensemble model which applied various Gabor representations as inputs during training and testing phases. This GDCNN containing two sections such as construction of GDCNN ensemble that builds members of GDCNN and combination of ensemble GDCNN(Choi & Lee, 2020). They have done the experimental analysis with public face databases along with evaluation protocols of related standards. The proposed method shows enhancement in face recognition. Identifying and recognizing faces increases the consideration over various fields for the past few years. The face contains higher information and is easily accessible during our day to day life that is used for many of the applications that need to be authenticated. However, face recognition methods are facing many challenges. Hence, many of the face spoofing detection systems are developed to sort out the above mentioned problem. In addition to this, **H.Chen et al. (2019)** planned to develop a model for counter face spoofing that adds both face detection and face spoofing. In this work, they developed a Face Anti- Spoofing Region- based CNN (FARCNN) that is based on enhanced region - based CNN (R-CNN) outline(Kaur & Digra, 2024). In the proposed model, the face spoofing is done by considering three classifications such as rear face, fake face and also its background.

The proposed model is optimized by extending with specific schemes that includes fusion of Region Of Interest - Pooling feature and the addition of actual multitask crystal loss function. The various illumination situations are handled by introducing Retinex based Local Binary Pattern for detecting face spoofing. At last, the detectors that are mentioned above are connected to attain the optimum performance by using the data bases such as CASIA-FASD, REPLAY-ATTACK and OULU-NPU.

In some of the unconstrained environments, it is still a tough challenge in recognizing facial expression due to the reason that the classical facial expression classifiers are concentrating only on identifying frontal face and they failed to deal with the partially occluded images that were also common in wild nature. Hence, **Y.Li et al. (2019)** developed Attention Mechanism based Convolutional Neural Network (ACNN) that is used to observe the occluded regions and also to concentrate on un-occluded regions. The proposed model is an end-to-end outline that associates the various representations of region of interest facial regions (ROIs)(Y. Li et al., 2019).

FACE RECOGNITION

The Figure 3 shown below explains the various comparisons of training and evaluation protocols of face recognition models. The diagram shows the training and evaluation protocols for facial recognition models, which encompass both face verification and face identification tasks. The process of Face Verification can be subject-dependent, in which the model compares and verifies the existence of an identity from the test set in the training set using a Label Predictor. To verify identities, the model extracts features using a Feature Extractor and compares distances if the identities are subject-independent, meaning they do not appear in the training set. The model also operates in subject-dependent mode in Face Identification by utilizing a Label Predictor to compare test identities to those in the training set. The identification process is further divided into close-set and open-set modes if the identities are subject-independent. In close-set, the model is limited to identifying identities in the training gallery, whereas in open-set, queries may include identities that are not in the gallery. This enables the model to identify unregistered identities through feature distance comparisons. These protocols offer a comprehensive framework for managing a variety of scenarios in face recognition duties.

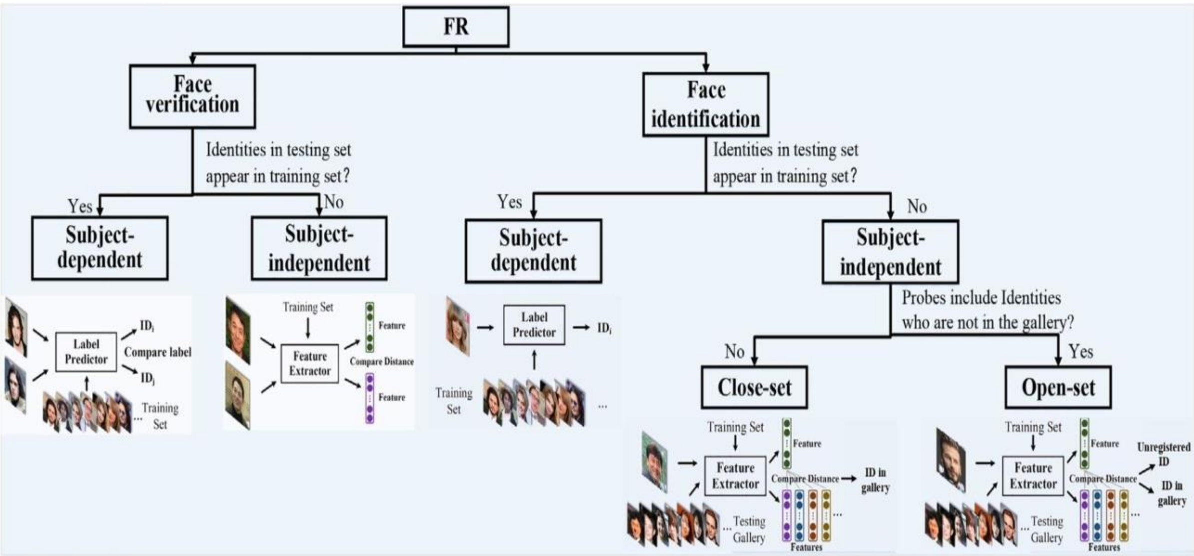


Figure 3. The various comparisons of training and evaluation protocols of face recognition models
Source: (Amato et al., 2019)

Based on the training protocol, the face recognition system is categorized as a dependent and independent subject that depends on the attributes used for the testing. Similarly, in testing, it's categorized as close and open set identification of face. With some face recognition systems, the recognition rate requires a specific sample for training. Keeping in mind, a new model called HoG-LDB (Histogram of Oriented Gradients - Local Difference Binary) was developed by **Wang.H.et al. (2019)**. After that, they added this model along with the Sparse Variation Dictionary (SVDL) in order to recognize the various facial variation images. The proposed descriptor used for edge feature extraction and for extracting local feature patterns of image. Finally, SVDL is implemented over a common training set to obtain a non-specific variation dictionary that is utilized to identify the images that are having variations. It is evident that the proposed system produces higher accuracy with AR database, Yale database and CMU- PIE database during the experimental analysis(H. Wang et al., 2019).

It is a well-known fact that recognizing faces is one among the practical applications of pattern recognition. Conversely, it is a big challenge for face recognition systems to deal with the images that are affected by various unrestrained conditions. **Hence Tong et al. (2019)** explained about the disturbance occurring in face recognition performance and also tried to teach with face symmetry. They combined the symmetry of Multi-mirror with LBP which is called Multi-Mirror Local Binary Pattern (MMLBP). In order to enhance the performance of face recognition, the proposed algorithm will do adaptive compensating with various lighting conditions and also they are used to extract the closer features over unrestrained conditions(Tong et al., 2019b). Hence, here Singular Value Decomposition Representation (SSVDR) is used instead of conventional LBP. It is proven with the experimental analysis that the proposed MMLBP is well enough to handle the images that are affected by various factors.

It has been a challenging task for the past few years to recognize faces from videos for computer vision applications. Face recognition from video is giving much information in order to enhance the accuracy rate when compared to the classical face analysis. But at the same time, it is suffered by variations of large scale, illumination and posture etc. **Zhang.Z et al. (2011)** developed a model and explained by separating this into Video-based and Video-video based systems that are analyzed in this work. Face recognition finds applications over various fields such as biometric security over video surveillance and also in various authenticated applications. Generally, non-linear shapes of faces exist because of their deformations over facial variations due to the various facial expressions. Hence, it is becoming a very tough task for face recognition and ends with poor recognition rates(Z. Zhang et al., 2011). The specific reason for this is a tens-degrees of freedom that exists in a non-linear space. Hence, in this work Peter. M et al. (2019) developed a model for non-linear kernel approach in 3D face recognition and showed the improved results with experimental results. Over the last few years, it is shown that convolutional neural networks are outperforming in face recognition. Here, **Ben.fredj et al. (2020)** explained an outline for learning a face recognition technique over an unrestrained environment with data augmentation that is destructive. Learning about noisy and occluded facial images is taken as their objective over large scale data. To achieve this, they combined losses of softmax and center layers as like supervision signals that in turn enhance the performance and also the final classification. The analysis is done with Labeled Faces of Wild and YouTube face data sets(Ben Fredj et al., 2021).

Identifying facial expressions for any kind of emotion is a simple task for humans, whereas it is a very tough task for computers. Even though the computers are detecting the emotions nowadays from images, **Mehendale.N et al. (2020)** developed a model known as Facial Emotion Recognition using CNN (FERC). This FERC is composed of two parts in which one is used to remove the background from the frame and the other is used for extracting features. In this proposed model, five various classifications of expressions are found by Expression Vector (EV). It used the data set of 10000 images of 154 persons and it could produce about 96% of accuracy. The two stages of the proposed model run in cascade mode which differentiates it from normal CNN and also helps to improve the accuracy. The experimental analysis is done with Caltech, CMU and NIST databases. Natural ways of communicating a human's emotional states are by expression of face. Over the past few years, an automatic Facial Expression Recognition (FER) was practiced in order to analyse the human behaviour during their interview panels, autonomous vehicle driving and in Bio medical treatments(Mehendale, 2020). **Gonzalez-Lozoya et al. (2020)** developed a model for recognizing facial expression which is based on extracted features over CNN with consideration of samples of pre-training(González-Lozoya et al., 2020). Keeping in mind, **Hong Hui et al. (2021)** developed a cascade light CNN that requires minimum hardware but gives good performance. In this work, they developed normalized Light CNN. In addition to the Light CNN, in this model they added one layer additionally for normalization in both training and testing that helps to represent the better output. The analysis was done with a LFW database that produces an accuracy of 98.46%(Zheng & Zu, 2018). Another paper by **Puja.S et al. (2019)** also discussed the complex architecture requirement for Deep Learning algorithm for face recognition was discussed and also the significant application of face recognition as biometric authentication was mentioned over here(Prasad et al., 2020). Here the main objective is to learn about face representations that are deep learning based over various unrestrained conditions(Prasad et al., 2020). They also mentioned about the models that are used for face representation extraction such as Light CNN and VGG-Face. This paper strongly insisted that the deep learning model is robust enough to deal with the occluded Images.The unique model called novel coupled mappings was developed by **Gao.G et al. (2020)** to handle low resolution faces using Deep CNN. Their model contains two classifications of DCNN's in ord er to match the higher and lower face image resolutions over a general spatial metric along with transformations that are non-linear. The higher layer contains 14 layers and the lower one has 5 layers that are mapped with a common space that comprises a 5-layer super resolution network(Gao et al., 2022).

Serign Modou et al. (2019) addressed the issues of face recognition for the images that are affected by pose, illumination etc and they developed a combined model of LBP and Advance techniques for Image processing that includes Adjusting contrast, Bilateral Filter, Equalization of Histogram and blending of images to improve an accuracy(Bah & Ming, 2020). The experimental results show the efficiency of the proposed model. A vital indication of identifying human behavior and attention, it is an important key factor to recognize and monitor position of head. Generally, this can be done by calculating landmarks of localized targeted faces and correcting the 2D issue by mean head model **Kewen Yan et al. (2017)** proposed a face recognition model that is based on CNN which contains convolution, fully connected and softmax layers.

In this paper, Stochastic Gradient algorithm is used for feature extraction and classification that helps to avoid the problem of over fitting. For training and testing, Convolution Architecture for Feature Extraction (Caffe) was used. The analysis was done with various datasets such as ORL and AR databases that provide 99.82% and 99.78(Yan et al., 2017). In the year of 2020, the authors **Gurlove Singh et al. (2020)** proposed a work related to face detection and recognition scheme with respect to digital image processing strategies. In this paper, the authors presented such as the most important probability to identify the person's face, with the help of face features only the person can easily be identified(Singh & Goel, 2020). Therefore, facial features and the associated processing techniques are developed to identify the person based on it. This work dictates the identification of face features with characteristic values and assists the process of authentication in a secure manner without any privacy flaws over web mediums. At that point the entire cycle is rehashed in this manner helping in building up a face acknowledgment model which is viewed as perhaps the most incredibly pondered biometric innovation. The authors had illustrated the overall process of face detection and recognition by means of two separate factors such as Face Detection and Face Recognition. In the process of face detection, the identity of the face is observed from the input image by means of the shape and structural position of the face. The second portion of Face Recognition identifies the identity of a person with respect to the already trained models. This work follows two individual methodologies to identify the facial features exactly such as: Eigen Face technique and the Principle Component Analysis (PCA) model.

The main concentration of this research is to exactly identify facial features and identify the person based on it as well as this paper giving more importance to digital image processing features. The major advantage found in this paper is that it uses the diverse algorithms to identify facial features exactly by means of Eigen face technique and the PCA methodology, in which these features provide high accuracy in results as well as provides better timing improvements.

Table 1 Summary of Datasets for Face Recognition Analysis and Sources

Source: (Alghamdi et al., 2020)

Sr.No	**Dataset**	**Images**	**Faces**	**Source**	**Type**
1.	AFW	205	473	Flickr	Images
2.	FDDB	2845	5171	Yahoo! News	Images
3.	IJB-A	24327	49579	Internet	Images / Videos
4.	MALF	5250	11931	Flickr, Baidu	Images
5.	AFLW	21997	25993	Flickr	Images
6.	PASCAL Faces	851	1335	PASCAL VOC	Images
7.	WIDER Face	32203	393703	Google, Bing	Images
8.	Wildest faces	67889	109771	YouTube	Videos

The number of images, number of faces, source, and form of media are among the main characteristics of the diverse datasets that are employed for face recognition analysis, as summarized in Table 1. The datasets encompass a wide variety of sources, such as search engines such as Google and Bing, social media platforms such as Flickr, and Yahoo! News. The objective of this table is to offer researchers an exhaustive overview of the available datasets, thereby facilitating comparisons and guiding selection based on the specific project requirements of face recognition applications. In the year of 2020, the authors **Jana Alghamdi et al. (2020)** proposed a paper related to facial feature identification and recognition strategy using diverse algorithms(Alghamdi et al., 2020). In this paper, the authors illustrated that the face features analysis and estimations are the systematic process and it is an information technology domain, in which it uses a diverse set of methodologies to detect the faces and recognize them by using digital image processing schemes. The authors specify the facial difference of the individual as well as check the caught pictures by contrasting them and the facial pictures put away in the information base. Face recognition scheme is a significant theme in system perspective and numerous analysers have examined this subject from multiple points of view; it is significant particularly in certain applications, for example, observation frameworks. The primary target of this review paper is to look at the numerous methodologies utilized for face features identification and recognition. In this paper, the authors cross checked their viewpoints with a diverse set of algorithms such as Neural Network, Adaboost logic and so on. So, that the research is producing a huge set of positive outcomes and it provides a way to further researchers to work on it. Usually this kind of survey works analyses the concept with single point of perception but in this paper lots of specifications associated with facial features are recognized and monitored with respect to different methodologies. The major focus identified from the paper is extracting the facial features with the help of diverse algorithms and provides the best accuracy in summary with the help of digital image processing logic.

3. METHODOLOGY

Face recognition is difficult to analyze and recognize photos in uncontrolled environments due to poor resolution, position variations, and intensity differences. Our suggested technique focuses on photos obtained in unconstrained situations since traditional methods are only careful about processing images in regular environments. Thus, the suggested model fixes blind image deconvolution. There are various ways to solve blind deconvolution problems, but retrieved invariant features are not adequate. The issues of identifying faces recorded in uncontrolled conditions are discussed here. Traditional approaches employ Local Binary Patterns, however they are not resilient and are not suitable for intensity fluctuations. Thus, just the blur component is originally considered and rectified by LOG filter. After pre-processing, Viola Jones method detects faces using Harr features and Ada Boost technique. The suggested approach Hybrid RPSM_CNN (HRPS_CNN) is utilized for feature extraction and classification, as illustrated in Figure 4. which shows the main blocks of the proposed face recognition method.

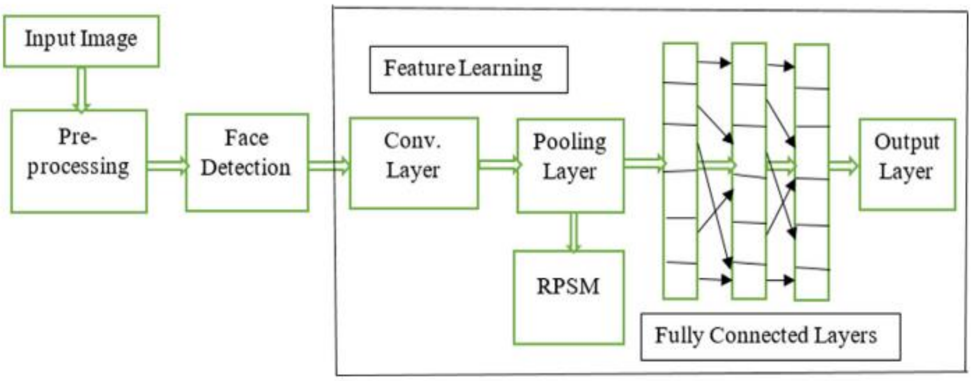


Figure 4. Block diagram of the Proposed Method
Source: (Tamilselvi & Karthikeyan, 2022)

In the proposed HRPSM_CNN method, three steps as mentioned below do the face recognition.

i. Pre-processing
ii. Viola Jones based Face detection
iii. HRPS_CNN face recognition

The images are taken for this experimentation is from IMM face data base, AR and ORL database. The facial images from the fore mentioned databases are subjected to the pre-processing by applying Gaussian Log filters to remove the external noises from the image and also to reduce the intensity of the pixels by detecting the edges of the frame. Next, the Viola Jones algorithm is utilized for detecting the face and then that image is subjected under HRPSM_CNN for extracting essential features and classification.

PRE-PROCESSING USING DBC

The images from AR and FERET databases are given as input and shown in Figures 5. and 6. (Figure 5. is taken from AR data set and Figure 6. is taken from FERET data set). The basic operations at the pre-processing stage such as gray scale conversion, cropping and resize are carried out over the images taken from data sets. The output images from this part are the same size and will be applied to the Directional Binary Code (DBC) operator. A DBC feature descriptor is used on an image in order to encode the directional edge information. DBC provides efficient pixel information for a given RGB color Image. Feature vector is extracted by comparing the pixel values of corresponding RGB channels of a given Input image. Pixel values are more confined within the boundary region, so the retrieval rate will be better than LBP

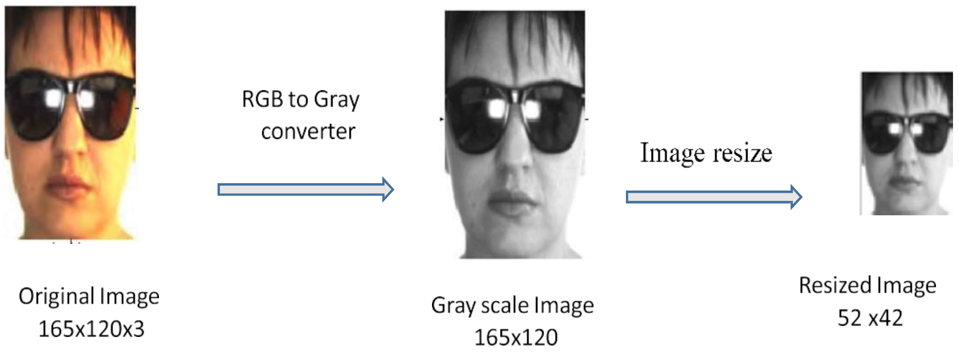


Figure 5. Pre-processing sample Image from AR data set

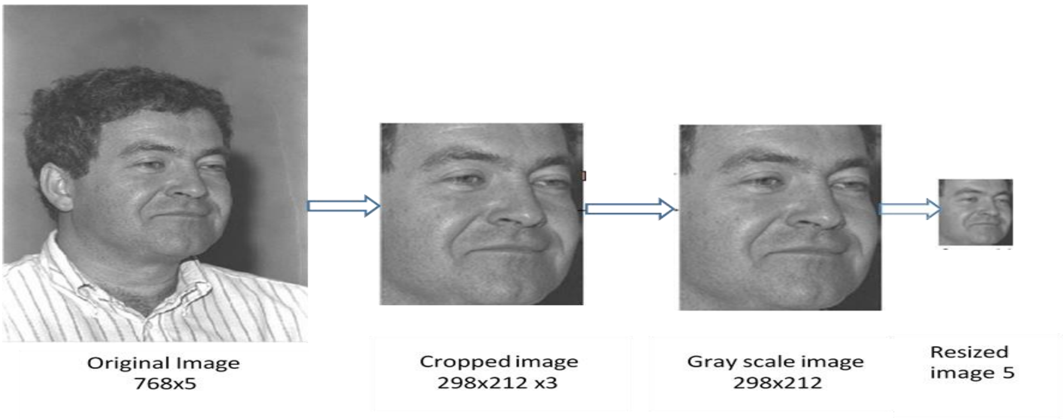


Figure 6. Pre-processing sample Image from FERET data set

In the general face recognition system, the primary step is pre-processing that is mainly done with the intention of removing noises. But this alone not enough when moving towards an efficient face recognition system.

Face Detection by Eigen Value Calculation

In the previous step, the Gabor filter is utilized for removing the non-face regions from the picture frame and also reduces the dimension of the same. This reduced dimension matrix structure is subjected to Eigenvalue calculation that in turn reconstructs the image. Here, the specific variations among the faces are identified that are called Eigenvalues of a face hence they are primary component of the faces like the eyes, ears, mouth and nose. Individual face is recognized by a sum of weighted Eigenvalues that is used to recognize a face by comparing the above said weighted sum of Eigenvalues with weighted values of reference faces that are well known already. The specific advantage of choosing the Eigenvalue based face detection is that it is capable enough to learn the specific features and to recognize the same after some time without any supervision which makes it very much suitable for Convolutional Neural Networks (CNN). Many of our face recognition systems fail to concentrate on extracting the features exactly that are important for recognition. Hence, in our work we proposed this method of encoding an image with the principal component values that are known as Eigenvalues are used. Those primary key features are not related to the face directly or indirectly. Simply we can say that, in order to detect the face, first we should extract the significant key factors as much as possible and compare them with the reference database created already. The Eigenvalues are taken as the principal components of the face. They can be taken as a pair of features in order to represent the differences among the faces. Every image position can be contributed high or low with each Eigenvector, hence they are known as Eigen faces. Each individual face is characterized as a linear mixture of Eigen faces and those having high variances among them are considered as “best” and with all these “best” Eigen faces, a subspace of dimension M is formed.

The Eigen value is calculated in following steps:

- Initially, the set of images are acquired from the datasets.
- Calculating Eigenvalues and finding the best Eigenvalue matrices based on the M dimensional space is created.

- The sum of weights is calculated for the features in M dimensional space and then combining them in a linear manner to identify the face. The non-face regions are removed.
- The same procedure is followed for the faces that need to be identified. If the same face is detected many times, then it can be incorporated to the known faces by calculating the weights. Let us consider a two dimensional image represented as J(x,y) with the size of the image is N X N for 8 bit and the image vector dimension is N^2. Since, the images are the same in overall structure; it is not possible to configure them in a large space of image whereas they can be configured in low dimensional space. The concept behind Principal Component Analysis (PCA) is finding the vectors that are used in distributing the face image over the entire frame space and forming subspace of face images. The calculation of Eigenvalues is explained with the flow chart given in Figure 7.

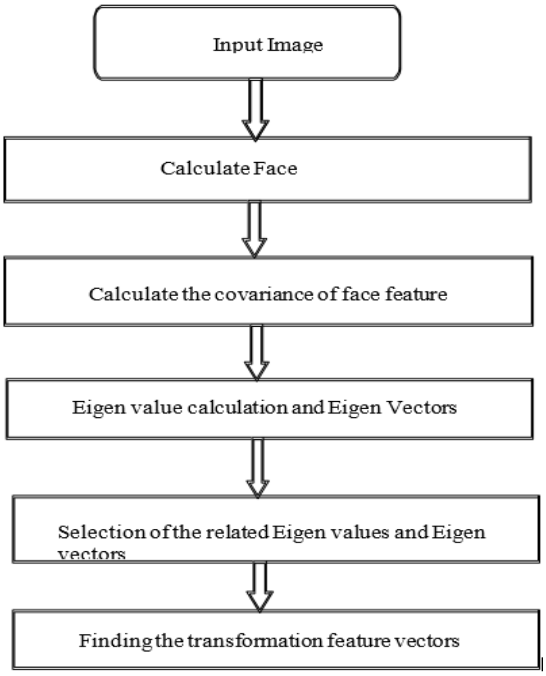


Figure 7. Flow chart of Eigen value calculation

The measured Eigen value describes the importance of extracting these features as a specific value in order to renovate the image. The image sharpness is ensured with the extracted normalized features.

The normalization process to calculate Eigen value is given by Equation (1)

$$g(x,y) = \frac{g(x,y) - \sum_{i=1}^{n} \sum_{j=1}^{m} g(x,y)}{\sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} [(x,y)]^2}}$$

The normalized value of g(x,y) is determined by subtracting the average of its values within a specified range. In this case, m m represents the total count of feature values, while n n denotes the total number of observations. The process is particularly beneficial in the computation of an eigenvalue in the context of reducing dimensionality or data representation, as it stabilizes data for subsequent calculations.

The computational mean operator is given in Equation (2) as

$$\mu = \frac{1}{N^2} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} g(x, y)$$

Defines the computational mean operator. In this context, $g(\ ,y)$ g(x,y) signifies the mean intensity across all pixels, while μ μ denotes the pixel intensity values in a given $N \times N$ N×N matrix. This equation determines the average pixel intensity by averaging the values of all pixels and dividing the sum by the total number of pixels, $N2$. This operation is indispensable for image processing and feature extraction applications, as it facilitates the examination of the image's general luminance or intensity characteristics.

Covariance matrix is given by the Equation (3)

$$S = \frac{1}{N-1} GG^T$$

From equation (1), G is a matrix of g(x,y) later mean removal (G = G-µ). From the calculated Eigenvalues, the feature descriptors that are weighted nearly equal to the similar weighted matrices and the matrices that are having much difference in the Eigenvalues are removed by considering those as non-face regions. After this step, the new weighted matrix of face detected images is sent to the CNN network for extracting features and to recognize the same.

Let us consider the face image set for training as Γ1, Γ2, Γ3 ΓM. The

Average of the face group is given in the Equation (4) given below

$$\boldsymbol{\Psi} = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n$$

This equation computes the average value Ψ of a collection of values Γ over M elements. The difference $\phi\ i = \Gamma\ i - \Psi$ ϕ i= Γ i−Ψ represents the deviation of each individual value $\Gamma\ i$ Γ i from this average, signifying how much each value differs from the mean. Collectively, these equations evaluate the central tendency and individual variance of a dataset.

The Eigenvalue calculation for face detection is explained with step by step flow where the Principal Component Analysis (PCA) is used to analyze and measure the association of every variable with their corresponding neighbor variables by calculating the Covariance matrix. Eigenvectors are useful in providing the information about the date spread within the region.

These vectors are then subjected to PCA that required pair of M orthonormal vectors Un, to define the distribution function as in Equation (5)

$$\lambda = \frac{1}{\sum_{n=1}^{M} (\mathbf{U}_n^T \boldsymbol{\varphi})}$$

The equation represents the sum of eigenvalues (λ) obtained from the distribution function defined by orthonormal vectors (Un) during Principal Component Analysis (PCA). Here, M denotes the total number of vectors, and $\boldsymbol{\varphi}$ represents the data vectors transformed by the orthonormal basis (U). This process helps in reducing dimensionality while preserving variance in the dataset.

Is maximum, whereas the Equation (6) is

$$\mathbf{U}^T\mathbf{U} = \delta$$

$$\delta_{ik} = \begin{cases} 1, & \text{if } i = k \\ 0, & \text{otherwise} \end{cases}$$

The Kronecker delta function, δik is represented by the equation. It is 1 when the indices i and k are equal, and 0 otherwise. In this context, it denotes that the operation $U\ T\ U$ generates an identity matrix, which suggests that the unit vectors represented by U are orthogonal or independent. This property is essential in a variety of mathematical and computational applications, particularly in signal processing and linear algebra, as it guarantees that distinct components do not interfere with one another.

Here Uk and scalars λk are representing corresponding Eigen vectors and Eigen values correspondingly.

The equations describe the covariance matrix CCC, calculated by summing outer products of feature vectors from a dataset, forming matrix AAA.

$$C = \frac{1}{M} \sum_{n=1}^{M} \boldsymbol{\varphi}_n \boldsymbol{\varphi}_n^T$$

$$C = \mathbf{A}\mathbf{A}^T$$

Equations (7) and (8) represent the covariance matrix C in this context, which calculates the covariance among features in a dataset. C is defined in the first equation as the sum of the outer products of each feature vector ϕ_n from sample. The matrix is composed of these feature vectors, and has dimensions of $N^2 \times N^2$. The eigenvalues and eigenvectors of the image dimensions are critical for a variety of applications, such as image compression and dimensionality reduction, and this matrix is essential for their determination.

The calculated Eigenvectors over the M dimensional space are considered and recognized further by training and classifying with the use of EVB_CNN. The face detection using Eigen value calculation is comprised as the following steps:

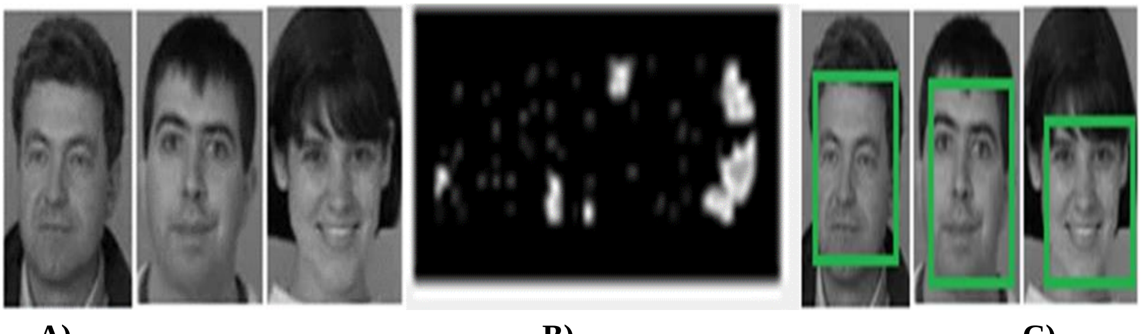
Let us consider a given unknown image is represented as Γ.

Step 1: Compute the value of $\varphi = \Gamma - \mathbf{\Psi}$.

Step 2: Compute the value of $\boldsymbol{\phi}' = \sum k\ Wi\ \mathbf{U}i$ where $Wi = \mathbf{U}T\boldsymbol{\varphi}$.

Step 3: Compute the value of $ed = \| \boldsymbol{\varphi} - \boldsymbol{\phi}' \|$

Step 4: If the distance $ed <$, then Γ represents a face.



A) B) C)

Figure 8. Detected face from Eigen value calculation (a) Input image from AR data set (b) Eigen values of the images (c) Detected face from the Image

The Figure 8. Depicts the sample image from AR database and also the face detected output after applying the Eigen vector.

EVB_CNN for Feature Extraction a nd Classification

A Convolutional Neural Network is a booming technology of Artificial Neural Network which finds significant applications over image recognition. It uses deep learning for performing specific tasks and using computer vision which includes image and video recognition along with natural language processing (NLP)(Sharma et al., 2024). The pictorial representation of the conventional face recognition process is depicted in Figure 9. As shown below.

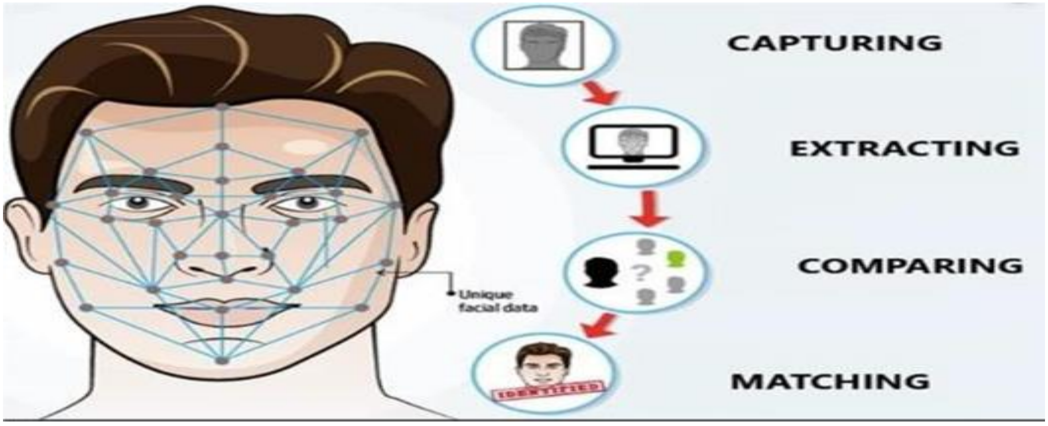


Figure 9. Pictorial depiction of facial recognition process

Convolutional Neural Networks (CNN) are playing a major role in face recognition nowadays, since it is very robust on handling the images that are suffered with noises and also with some unconstrained environments. In CNN, it is easy to learn about the elements from previous experiences and can be used to recognize the same in future if it needs to be under unsupervised control.

4. RESULT

For experimental analysis, in our proposed work the Aleix Martinez and Robert Benavente (AR) database and FERET database are used. The databases were processed for both the training and testing phases on a system equipped with a 1024x768 resolution monitor, a 10th generation Intel Core i5 processor, 8 GB RAM, and a 500 GB hard drive. Simulations were conducted using MATLAB 2019, including the necessary toolboxes for deep learning techniques. Additionally, an NVIDIA GPU with CUDA support was utilized to accelerate the deep learning computations.

a) **AR Dataset:** The AR face data set is used for the experimentation purpose in our proposed method since this AR data set contains the faces with unconstrained environments such as lighting, occluded images with accessories, facial changes, etc. In this data set, there are 3276 images where the classification is done for 126 subjects that include the images of 76 men and 56 women that are taken over various lighting conditions. The Figure 10. Depicts the sample image of the AR data set.

Figure 10. Sample of images from AR database for 1 subject

The table compares two facial image datasets, AR and FERET. AR contains 3,276 images of 126 subjects in BMP format (768x576 pixels) and includes accessories like glasses, masks, and beards. The FERET dataset has 14,126 grayscale images of 1,199 subjects, with dimensions of 256x384 pixels. AR images capture frontal faces, while FERET includes faces turned between -90 to +90 degrees. Both datasets include variations in illumination, blur, facial expressions, and occlusion. The image is a sample from the AR dataset, showing 26 images of one subject, demonstrating different facial expressions, lighting changes, and occlusion (using glasses and scarves). A proposed face recognition algorithm achieved 95% accuracy under occlusion and reduced computation time significantly.

b) **FERET data set:** It also contains the images taken with various unrestrained conditions such as pose variation, lighting and facial expressions. There are 14126 images that correspond to 1199 subjects. Like the AR data set, there is no constraint for sample size of each subject. The sample size for an individual subject may vary from 5 to 90. The images stored in this data set are in PMM format and the size of the image is 256 X 384 pixels.

c) **Experimental analysis:** The proposed method was analyzed by calculating the error rate and misclassification rates and they are depicted using the graphical representation. The AR and FERET data sets are used in the proposed method for analyzing the performance of accuracy. The values given in Table 1 is showing the variation of error rates along with epoch number. From the AR and FERET data set the 80:20 ratios of images are considered for training and testing. The analysis was done with two sets of data to ensure the improvement in the accuracy. The error rate is given the findings of frequent occurring errors in feature extraction and the misclassification value giving the value of the ratio between trained image and to the actual image. These two parameters are important in convolutional neural networks in order to ensure the efficient face recognition accuracy.

Figure 11. Sample Images from FERET Dataset

Figure 11 displays sample images from the FERET dataset, which is commonly used for facial recognition research. The dataset contains grayscale images of various individuals, capturing different facial expressions, angles, and lighting conditions, aiding in the evaluation and training of facial recognition algorithms.

5. CONCLUSION

The research investigates the integration of CNN-based face recognition technologies into student management systems, with an emphasis on bridging both technical and ethical barriers. It emphasizes the use of face recognition technology backed by AI algorithms like AdaBoost and Convolutional Neural Networks to automate and improve administrative activities like as attendance monitoring, access management, and tailored student engagement. By reducing manual operations, this technology increases educational institutions' efficiency, accuracy, and security. One significant difficulty noted is the ethical consideration of privacy, data security, and possible biases inside algorithms. The research underlines the need of openness, fairness, and adherence to privacy standards in safeguarding students' sensitive data. It also emphasizes the need of addressing technical problems such as dealing with various surroundings and enhancing algorithmic accuracy in order to ensure successful deployment. To address these issues, the article suggests a systematic strategy for incorporating face recognition into student management systems. This involves preprocessing picture data, using Viola-Jones methods for detection, and using sophisticated CNN models such as HRPSM_CNN for feature extraction and classification. The proposed system leverages datasets such as AR and FERET to illustrate its accuracy, which exceeds 95% under difficult settings while incurring low computing costs. The research finds that, although CNN-based face recognition has great potential for enhancing student management systems, its effective deployment needs a delicate balance of technical innovation and social responsibility. The suggested approach eliminates biases, improves accuracy, and protects privacy, opening the path for ethical use of this technology in educational contexts. Future research is recommended to improve algorithms, broaden testing in real-world settings, and guarantee inclusive and fair applicability to various student groups.

FUTURE SCOPE OF THE STUDY

Research on CNN-based facial recognition for student management systems presents opportunities for advancements in educational and technological fields. Future studies could improve algorithmic accuracy by addressing environmental and demographic challenges. Developing hybrid CNN architectures or advanced attention mechanisms can enhance recognition rates, particularly in settings with variable lighting, occlusions, and movement. Integrating multi-modal biometrics, such as combining facial recognition with voice or gait analysis, offers greater security and robustness, reducing errors from single-mode systems. Strengthening data encryption techniques will ensure student data security, aligning with global privacy laws and ethical standards. Ethical considerations demand further research to establish transparent and fair frameworks, addressing algorithmic bias and promoting inclusivity across diverse populations. The adoption of edge computing and IoT integration can optimize system efficiency, enabling real-time processing and scalability in large campuses while reducing dependency on centralized servers. User experience enhancements, such as intuitive interfaces and seamless integration with existing administrative tools, will support adoption by non-technical stakeholders. Pilot testing across institutions can uncover practical deployment challenges and solutions. explainable AI (XAI) approaches could be explored to improve transparency, enabling users to understand system decisions. These directions will help create ethical, efficient, and inclusive systems that meet the evolving needs of educational institutions.

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