Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.17.(2) 2025,pp.Comp 202–214

Available online at www.qu.edu.iq/journalcm
JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS
ISSN:2521-3504(online) ISSN:2074-0204(print)

Appling XGBoost for Advanced Face Recognition System

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A R T I C L E I N F O

Article history:
Received: 19 /04/2025
Rrevised form: 12 /06/2025
Accepted : 16 /06/2025
Available online: 30 /06/2025

Keywords:

Face Recognition, Security, XGBoost, Machine Learning, DeepFace.

A B S T R A C T

Face recognition technology has significantly advanced and become essential in various applications, including security systems, human-computer interaction, and biometric authentication. This work introduces an effective face Recognition for recognizing a person from facial images. This work utilizes state-of-the-art preprocessing and augmentation techniques, histogram equalization, Gaussian blur, and Canny edge detection in enhancing quality and diversity within the data. These will ensure that all facial features are captured, including those extracted by Deep Face, HOG, LBP, and Gabor filters. Some of the machine learning methods applied and tested on this CAS-PEAL dataset include XGBoost, Decision Tree, and Random Forest. Of these, the best performance was by XGBoost, at near perfection. The outcomes hereby show that an efficient fusion of multi-feature extraction approaches with the recent machine learning methods improves the reliability of face recognition against every change in environmental conditions.

https://doi.org/10.29304/jqcsm.2025.17.22197

1. Introduction

Face recognition technology has advanced significantly in recent years, playing a crucial role in security systems, authentication processes, and human-computer interaction. It identifies or verifies individuals in static images or video frames by comparing them to a pre-stored database of faces [1]. With its numerous applications in authentication, security, surveillance, and human-computer interaction [2], face recognition has increasingly become important. Face recognition is commonly categorized into two groups: geometric feature-based and appearance-based methods [3]. Feature-based geometric methods, such as elastic bunch graph matching [4] and active appearance models [5], analyze spatial relations of facial features. On the other hand, appearance-based methods utilize intensity or extracted parameter values to identify faces [1]. A face recognition system operates in two most crucial phases: face detection and face identification [2]. Face detection detects and extracts facial information from an image or video, while face identification matches the identified face with the stored database to verify or identify. In the step of face detection, facial regions are discovered and identified in a given image. Next is the step of face identification, wherein the face-detected objects are matched against people known to the system

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that have been stored there. Therefore, developing effective algorithms for both face detection and identification is essential [6]. However, face recognition presents several challenges due to variations in factors such as lighting, pose, identity, facial expression, hairstyle, aging, makeup, and image scale. Even for humans, recognizing faces accurately under poor or extreme lighting conditions can be difficult, as the same individual may appear noticeably different [7]. One widely used approach to mitigate pose-related issues in face recognition is the view-based method, which involves capturing images of individuals from multiple angles to enhance recognition accuracy [8]. The advancement of biometric technologies, particularly facial recognition, plays a vital role in the development of smart cities. Researchers and engineers around the world continue to improve the accuracy and resilience of these systems, aiming to make them more dependable for everyday use. While passwords remain the most common form of authentication, the evolution of information technology and security algorithms has led to the integration of multiple biometric factors in modern recognition systems [9,10]. Biometric authentication relies on unique physiological or behavioral traits to identify individuals, offering several benefits—chief among them is the convenience of not needing to remember passwords or codes, as recognition can occur simply by standing in front of a sensor. In this case, various biometric modalities such as iris scanning, fingerprints [11], voice recognition [12], and facial recognition have become the order of the day in recent years. Biometric identification based on biological traits is very popular because it is very easy. Human being's face with its innate structures and patterns has made facial recognition the most widely applied biometric authentication tool in the past decade. Its applications span various fields, including surveillance, home security, and border control [13,37]. It is increasingly being utilized as a method of identification beyond smartphones, with applications in airport entries, sports arenas, and concerts. One of its key advantages is that it operates without human intervention, allowing individuals to be identified solely through images captured by cameras. While existing biometric systems employ various search techniques to achieve high identification accuracy, there is still a need for further development to meet real-time processing constraints. The immense volume of data, coupled with rapid advancements in artificial intelligence, has rendered traditional computing models inadequate for managing complex tasks like feature extraction. Consequently, innovative approaches are necessary to enhance the efficiency and speed of facial recognition systems. The aims of this paper are developing a robust face recognition system capable of accurately identifying individuals from facial images. Implement advanced image preprocessing and augmentation techniques to enhance data quality and diversity. Utilize multiple feature extraction methods to capture comprehensive facial features. Evaluate a variety of machine learning and deep learning models to determine the most effective approach. Assess model performance using standard evaluation metrics and identify areas for improvement. Despite vast progress in face recognition technology, the existing systems remain fundamentally limited in real-world settings. These are in the nature of compromised performance under varying lighting conditions, pose variations, facial expression changes, and occlusions, and challenges in achieving real-time performance on large and diverse datasets. Traditional methodologies are typically grounded in a single feature extraction technique or classifier, thus limiting their ability to generalize across environments. Besides, most systems are not robust enough to register delicate facial structural variations between populations. There is thus an acute need for a more adaptable and robust face recognition method with high accuracy regardless of volatile circumstances and taking advantage of multiple feature descriptors as well as advanced machine learning algorithms. This paper proposes a new face recognition system based on the application of XGBoost, an efficient machine learning algorithm, in combination with a mixture of advanced feature extraction techniques like DeepFace, Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Gabor filters. The system also employs top-class preprocessing and data augmentation methods like histogram equalization, Gaussian blur, and Canny edge detection to optimize the quality and diversity of training data. The proposed approach is evaluated on the CAS-PEAL database and indicates that the strategic combination of multiple feature extractors with XGBoost significantly improves recognition rates, even with challenging variations in lighting, pose, and expression. The fusion-based solution proposed here provides a strong and scalable alternative to existing face recognition systems.

2. Related Work

Xu et al. proposed an advanced face recognition system for power system safety management through the fusion of Convolutional Neural Networks (CNN), eXtreme Gradient Boosting (XGBoost), and model fusion techniques. Their approach takes advantage of the growing number of monitoring cameras and artificial intelligence development to enhance safety monitoring at workplaces. The system architecture is structured in three stages: firstly, preprocessed face images are fed into a CNN for high-level feature extraction and initial recognition probabilities. Secondly, features extracted are fed into an XGBoost classifier for another set of recognition probabilities. Finally, a model fusion method combines the two sets of probabilities to obtain the final recognition result.The experiment results demonstrated that CNNs are excellent at learning discriminative face features, and incorporating XGBoost enhances classification performance owing to its strength in modeling complex, nonlinear interactions. The model fusion also achieves greater recognition accuracy than individual models. Their system achieved greater accuracy than other state-of-the-art face recognition techniques. Additionally, the authors also illustrated real-world applications of their model, such as intruder detection and tracking operator trajectories, toward improved safety and reduced management costs in power system environments. This paper illustrates the complementary benefits of coupling deep learning-based feature learning with gradient-boosted decision tree classifiers such as XGBoost, reconfirming the effectiveness of such hybrid models for high-stakes real-time biometric systems [29]. Punuri et al. introduced a novel approach to Facial Emotion Recognition (FER) by introducing the EfficientNet-XGBoost model, where they leveraged the strengths of both deep learning and gradient boosting through a transfer learning architecture. Realizing the extreme importance and wide applicability of FER, researchers came up with a cascaded architecture based on EfficientNet—a new state-of-the-art convolutional neural network for feature extraction—and XGBoost for precise emotion classification. The proposed model adds features such as global average pooling, dropout, and dense layers to avoid issues like vanishing gradients and to accelerate learning. By the deployment of EfficientNet and replacement of its upper dense layers by an XGBoost classifier, the model well bridges the gap between deep feature extraction and interpretable decision tree-based classification. Visualization of feature maps confirmed the compression of feature vector size without discriminative information loss in emotion detection. Geometric data augmentation techniques were employed to address the issue of data imbalance, particularly for datasets like CK+ and FER2013. The model was rigorously experimented on a number of benchmark FER datasets, like CK+, KDEF, JAFFE, and FER2013. It performed extremely well with a best accuracy of 100% on CK+, and also on others, performing much better compared to analogous FER approaches. this work demonstrates the effectiveness of hybrid models that tap the deep representational power of CNNs and classification expertise of XGBoost. The results vindicate the effectiveness of such blends in achieving state-of-the-art performance in facial emotion recognition, even with imbalanced and heterogeneous datasets [30].

Ismail et al. proposed a novel improved deepfake video detection framework upon a hybrid model named YOLO-CNN-XGBoost, which was established due to the emerging trend and credibility of face-swapping deepfake videos. There are three main modules implemented in the system: YOLO for efficient face detection within video frames; InceptionResNetV2 as a deep convolutional neural network for detecting features; and XGBoost as the last classifier for classifying between real and fabricated faces. In this pipeline, the YOLO detector isolates facial regions from each frame so that only regions of interest are processed. InceptionResNetV2 then extracts deep features from these face images that encode fine details to allow accurate classification. XGBoost then makes the final decision using these high-level features, leveraging its ability to handle structured input data and model complex nonlinear relationships. The model is transferred to the combined CelebDF-FaceForensics++ (c23) and was able to report good performance with 90.62% AUC, 90.73% accuracy, and close-to-competitive precision, recall, and F1 scores. The findings confirm the merit of using CNN-based deep features coupled with XGBoost classification strength, as some of the current techniques are surpassed. This work uncovers the potential of hybrid deep learning and boosting-based approaches in video-based facial forensics, with particular value when subtle differences between real and manipulated content are essential [31]. In research on human face recognition for an attendance marking system, Nikhil et al. compared the accuracy of the Inception algorithm with the LGBM (LightGBM) method. 38 samples were used in the study, split into two groups of 19. Group 1 utilized the Inception approach, while Group 2 utilized the LGBM approach. Inception model was constructed after a dataset import in this study with Google Colab. The sample size was calculated using a previous study's values through internet statistical analysis tools, where pretest power stood at 80% and the alpha was fixed at 0.05. With statistical relevance of $p = 0.020$ ($p < 0.05$), simulation outcomes visualized the Inception algorithm displaying an accuracy percentage of 88% and LGBM algorithm providing a larger accuracy percentage of 97%. According to such findings, LGBM is a better approach compared to Inception in respect to face detection accuracy and forecast capability for such a dataset [32]. Tien et al. proved hybrid models' ability to differentiate real and counterfeit pictures. Hybrid model design is composed of two phases: feature extraction phase is the first, and image classification is the second phase. In the feature extraction phase, real and fake images are both provided to feature extraction according to a pre-trained CNN model (VGG16). Two high-end machine learning models, XGBoost and LightGBM, are used to classify the images during classification. The two hybrid models, VGG16-XGBoost and VGG16-LightGBM, originate from this practice. The test datasets that were utilized to check the model included images of forged faces that were gathered on the Flickr social network, edited by expert Photoshop editors, and automatically generated using GANs. Experimental results show that the model VGG16-LightGBM worked better than the model VGG16-XGBoost in identifying real versus fake images [33].

3. Classification of Face Recognition Systems

Face recognition is not as effective or dependable as other biometric systems, such as those based on fingerprint, eye, or iris recognition [11]. Notwithstanding its benefits, this biometric technology has a number of drawbacks because of different difficulties. Even while recognition in controlled settings has advanced significantly, problems still exist in uncontrolled settings because of things like age, dynamic backdrops, lighting fluctuations, and facial emotions, among other things. Using a variety of databases, this survey study examines the most recent face recognition methods created for controlled and uncontrolled settings. A number of methods have been put into place to recognize faces in 2D and 3D pictures. Based on their detection and identification techniques, we divide these systems into three primary categories in this review: (1) local, (2) holistic (subspace), and (3) hybrid approaches (Fig.1). The first method ignores the complete face in favor of concentrating on particular facial traits. The second method projects the entire face onto a smaller subspace, also known as the correlation plane, after processing it as input data. The third method improves facial recognition accuracy by combining local and global characteristics.

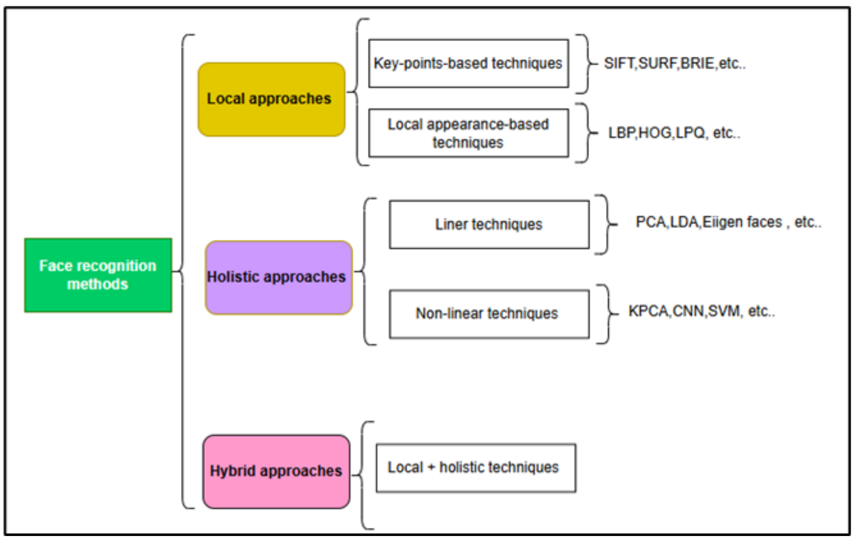

Fig.1-Face recognition methods.

4. Systems of Face Recognition

It is necessary to list the main issues that need to be resolved in order to guarantee correct performance before going into the methods utilized in face recognition. According to earlier research [14,15,16,17,18,19], a successful face recognition system should have a number of essential characteristics, including the capacity to process both images and videos, real-time performance, resilience in a range of lighting conditions, independence from personal traits (like gender, hair, or ethnicity), and the ability to identify faces from various perspectives. Facial data is collected using a variety of sensor types, such as RGB (Red, Green, Blue), depth, EEG (Electroencephalography), thermal, and wearable inertial sensors. These sensors improve the accuracy of face recognition by adding details to both still photos and moving video clips. Additionally, by tackling important issues including head posture, facial expression, and lighting fluctuation, three primary sensor types can aid in enhancing the dependability of face recognition systems. Audio, depth, and EEG sensors are examples of non-visual sensors that supplement visual input and improve identification reliability, especially when there are changes in lighting or location. Eye trackers and other small facial movements are detected by detailed-face sensors, which aid in distinguishing facial characteristics from background noise. Sensors with a target focus this group includes infrared thermal sensors, which help to improve identification in a variety of lighting settings and filter out visual information that isn't relevant. Face recognition systems may become more accurate and resilient in a variety of settings by utilizing these cutting-edge sensor technologies. A robust face recognition system typically involves three fundamental steps: (1) face detection, (2) feature extraction, and (3) face recognition, as illustrated in Fig.2 [20].

a) Face Detection – This is a step that identifies and detects human faces in a frame or image captured by the system.
b) Feature Extraction – Once a face is detected, significant facial features are extracted and are represented as feature vectors.

c) Face Recognition – Such features thus obtained are matched with a face template database in order to identify the person.

All these steps play a crucial role in ensuring the accuracy and effectiveness of face recognition systems.

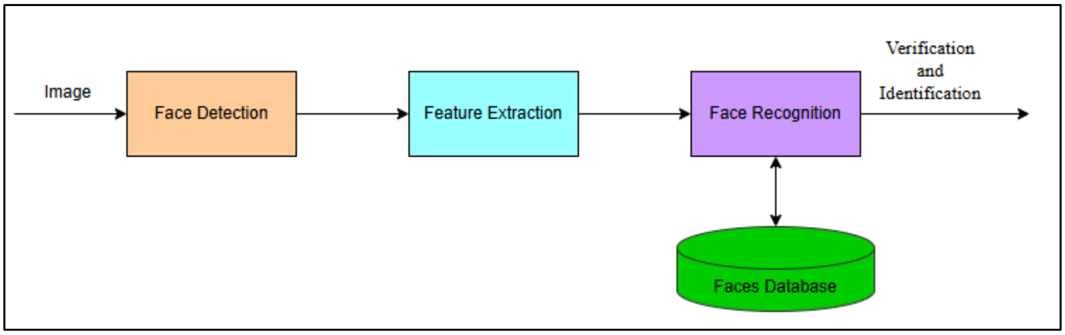

Fig.2-Structure of Face recognition [20].

1. Face Detection: Face recognition begins with detection and identifying human faces in a given image. The first step checks for any human face in the provided image. However, reliable face recognition may be degraded by changing illumination conditions and facial poses. Pre-processing methods are employed to enhance the robustness of the recognition system. For face localization and detection, several methods are commonly employed, e.g., principal component analysis (PCA) [25,26], histogram of oriented gradients (HOG) [23,24], and Viola–Jones detector [21,22]. Face detection is equally required in most applications, including region-of-interest detection, object recognition [27], and video and image classification [30].
2. Feature Extraction: Extracting features from the identified images of their faces is the main purpose of this stage. It represents each face using a feature vector, often referred to as a "signature," which captures the distinctive characteristics of the face, including the mouth, nose, and eyes, along with their geometric distribution [28].
3. Face Recognition: In this step, the features extracted from the face during the feature extraction phase are compared with known faces stored in a database. The two organizations primary uses of face recognition are usually identification and verification. Finding the closest match between a test face and a collection of faces is the goal of the identification phase. To decide whether a test face should be allowed or denied during the verification phase, it is compared to a particular face in the database [16].

5. Methodology

Construction of the face recognition system involves some key steps: data collection, preprocessing, augmentation, feature extraction, model building, and testing.

5.1 Dataset

The CAS-PEAL face database was built by the ICT-ISVISION Joint Research & Development Laboratory (JDL) of Face Recognition in collaboration with ISVISION Technologies Co., Ltd. and the National Hi-Tech Program. The PEAL face database was built having the following main goals in mind:

a) Giving facial recognition (FR) researchers access to a sizable dataset for algorithm evaluation and training.
b) Improving face recognition by providing a varied collection of photos with differences in Pose, Expression, Accessories, and Lighting (PEAL).
c) Progressing cutting-edge FR technology, with an emphasis on useful applications for oriental face characteristics.

As of right now, the CAS-PEAL database includes 99,594 photos of 1,040 people (595 men and 445 women), with changes in lighting, accessories, stance, and emotion. Nine cameras placed on a horizontal semicircular shelf take pictures in one shot at the same time to catch various poses. Subjects are also instructed to gaze up and down, which results in two photos totaling eighteen photographs. Five different face expressions, six accessory kinds (three pairs of glasses and three hats), and fifteen distinct lighting orientations are also included in the dataset. On a case-by-case basis, a portion of the database called CAS-PEAL-R1—which includes 30,871 photos of 1,040 subjects—is made partially available for study. JDL maintains the copyright for all photographs and acts as the technical agent for database distribution [34].

Fig.3-Setup of the photographic room.

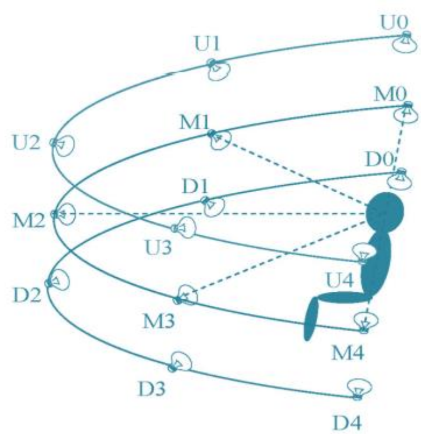

Fig.4-Composition of lamps and numbers.

Fig. 4 show “U,” is “upper,” “M,” is “middle and “D” is "down,” denote the rough positions of the lamps.

Fig.5-The CAS-PEAL

Fig. 5: A single individual is shown in 27 photos taken under various poses in the CAS-PEAL database. Nine cameras (C0–C8) positioned on a horizontal semicircular arm are used to capture the pictures. To get a variety of facial angles, the subject is told to gaze up, down, and straight into camera C4.

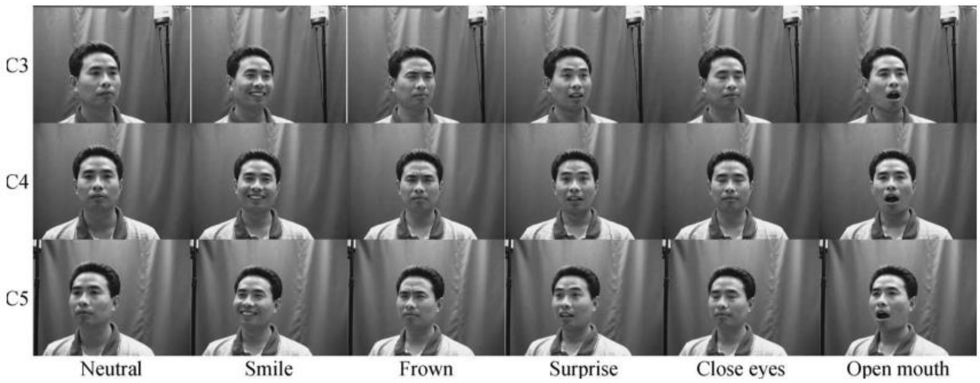

Fig.6- Examples of a single individual in three different stances with six different emotions (from cameras C3, C4, and C5).

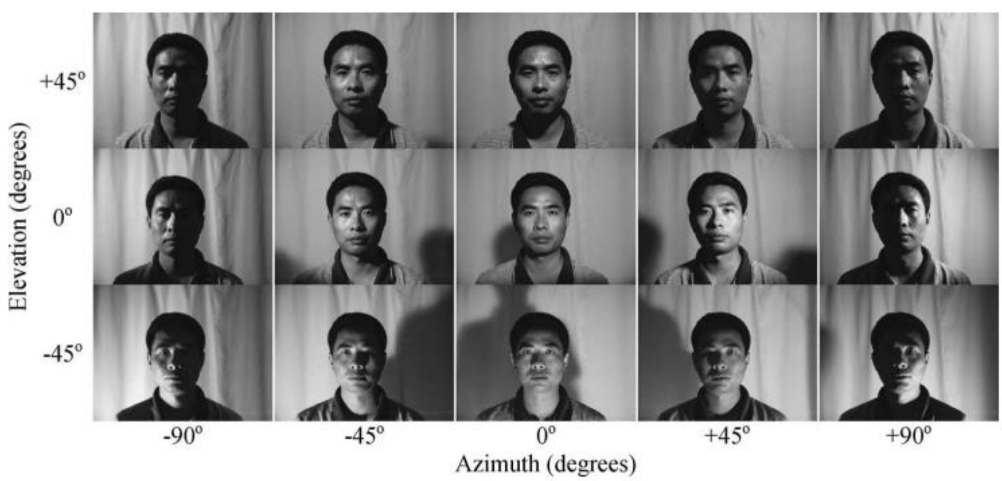

Fig.7-Sample photos of a single subject lit by a fluorescent light source at a variable height and azimuth from camera C4.

5.2 Data Preprocessing

To prepare the images for analysis, several preprocessing steps are applied:

1. Resize Images: To standardize input dimensions, OpenCV is used to scale all photos to 224x224 pixels.
2. Convert to Grayscale: Grayscale conversion of images preserves important information while lowering computing complexity.
3. Histogram Equalization: Enhances the contrast of images by spreading out the most frequent intensity values.
4. Gaussian Blur: Applies a 5x5 Gaussian kernel to reduce noise and detail in the images.
5. Edge Detection: Uses the Canny edge detection algorithm to highlight edges, which are important features for recognition.
6. Normalization: Pixel values are normalized to the range [0, 1] to standardize the input scale.

The preprocessing is implemented in the function preprocess_data(X, y).

5.3 Data Augmentation

To increase the size and diversity of the dataset, data augmentation is performed using Keras' ImageDataGenerator:

- Rotation Range: Images are rotated randomly within a 20-degree range.
- Shift in Width and Height: Pictures may be moved up to 20% in both the horizontal and vertical directions.
- Shear Range: Shear changes are implemented up to 0.2 shear intensity.
- Zoom Range: Up to 20% zoom is applied to images.
- Horizontal Flip: Randomly flips images horizontally.
- Fill Mode: Uses nearest pixel values to fill in new pixels created during transformations.
- Each original image generates 5 augmented images, significantly expanding the dataset.

5.4 Feature Extraction

The system provided is part of a face recognition system, which involve various feature extraction techniques like DeepFace, HOG (Histogram of Oriented Gradients), LBP (Local Binary Patterns), and Gabor filters.

a) Feature Extraction using DeepFace: extract_features_deepface function converts the input image to RGB if necessary, resizes it, and extracts facial features from it using the DeepFace library. The extracted features are appended to a list called features. DeepFace is a deep learning-based facial recognition library.
b) Combining Features: The function combine_features merges various types of features, e.g., HOG, LBP, Gabor filter, and DeepFace features, into a single feature vector using the concatenate function of NumPy.
c) Building a Decision Tree Classifier: The create_decision_tree function initializes a DecisionTreeClassifier, a machine learning model for classification. The model classifies an input image into a class based on the combined features.
d) Prediction Pipeline: predict_single_image function takes a trained model, image path, and class names as input. It reads the image, resizes, and extracts features using a feature extraction pipeline. It uses PCA (Principal Component Analysis) to reduce the dimension of the feature vector. It predicts the class of the image using the model and returns the predicted class name and confidence score.
e) Model Training and Saving: After the face recognition pipeline is executed on a dataset, the best performing model is saved as "best_face_recognition_model.h5". The code also demonstrates how to load the saved model and use it to predict the class of a test image.

6. XGBoost Model Development

XGBoost is a robust machine learning model, belonging to the gradient boosting type of algorithms, which is a form of ensemble learning. It employs strategies for regularization along with decision trees as weak models. It is highly computationally efficient with robust missing data handling, efficient feature importance analysis, and accelerated processing and scalability. Because of its versatility, XGBoost is generally used for various applications such as ranking, classification, and regression. In this article, we present a useful use case and an introduction to the XGBoost model [36].

7. Evaluation

Models are evaluated using several performance metrics [35]:

Accuracy:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Where TP is True Positive, FP is False Positive, TN is True Negative and FN is False Negative.

8. Results

These results show in table 1 that XGBoost performed the best with perfect accuracy, followed by Random Forest and LightGBM, both achieving 98%. The Decision Tree had the lowest accuracy at 82%, while Gradient Boosting was at 95%.

Table 1-Result of algorithms.

Algorithms	Accurcy
Random Forset	98%
XGBoost	100%
Dission Tree	82%
LightGBM	98%
Greadient Boosting	95%

Table 1 compares the performance of five different machine learning algorithms applied to the face recognition task. A brief description of each algorithm is provided below to contextualize the performance results:

- **Decision Tree**: A simple and interpretable classification model that splits data into subsets based on feature values. While easy to understand, it often lacks robustness and generalization in complex datasets.
- **Random Forest**: An ensemble of multiple decision trees that improves accuracy and reduces overfitting by aggregating the predictions of many randomized trees. It offers better performance than a single decision tree.
- **Gradient Boosting**: Is a powerful ensemble learning technique that builds a strong predictive model by sequentially combining multiple weak learners, typically shallow decision trees. Each new tree is trained to minimize the residual errors made by the ensemble of previous trees. This method excels in capturing complex, non-linear patterns in data, offering high predictive performance. However, it can be computationally intensive and sensitive to noisy data, making careful hyperparameter tuning and regularization essential for optimal results.
- **XGBoost (Extreme Gradient Boosting)**: An optimized implementation of gradient boosting that includes advanced regularization, missing value handling, and efficient computation. It is widely used for its high accuracy, scalability, and speed.
- **LightGBM**: Is an advanced gradient boosting framework specifically designed for high efficiency and scalability on large datasets. It employs a leaf-wise tree growth strategy, which allows it to reduce loss more effectively than level-wise methods like those used in traditional boosting frameworks. LightGBM supports categorical features natively and uses histogram-based decision rules for fast training and low memory usage. Its superior speed and accuracy make it a strong alternative to XGBoost, especially in environments where computational resources or training time are limited.

These algorithms were evaluated based on their accuracy in classifying facial images from the CAS-PEAL dataset. The results indicate that **XGBoost achieved the highest accuracy (100%)**, highlighting its suitability for high-dimensional, multi-feature input common in face recognition tasks.

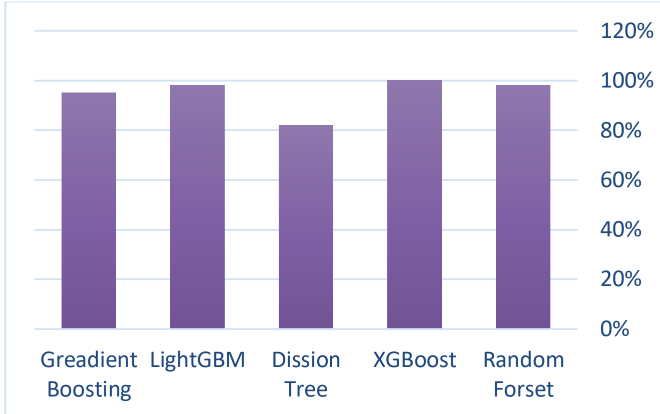

Fig.8- Result of algorithms.

The fig. 8 shows a confusion matrix, a common performance evaluation tool in machine learning, which helps assess the quality of a classification model by comparing actual versus predicted labels for each class.

Here's how to interpret the confusion matrix: The diagonal elements (from top-left to bottom-right) represent correct predictions (i.e., where the predicted class matches the actual class). Off-diagonal elements show misclassifications (i.e., where the model made incorrect predictions). In this confusion matrix:

Class 0: 11 correct predictions, 0 misclassifications, Class 1: 10 correct predictions, 0 misclassifications, Class 2: 11 correct predictions, 0 misclassifications, Class 3: 16 correct predictions, 0 misclassifications, Class 4: 8 correct predictions, 1 misclassification to class 5 and Class 5: 5 correct predictions, 1 misclassification from class 4.

Overall, the model performs well for most classes, except for some confusion between class 4 and class 5. This suggests that the model may struggle differentiating between these two classes.

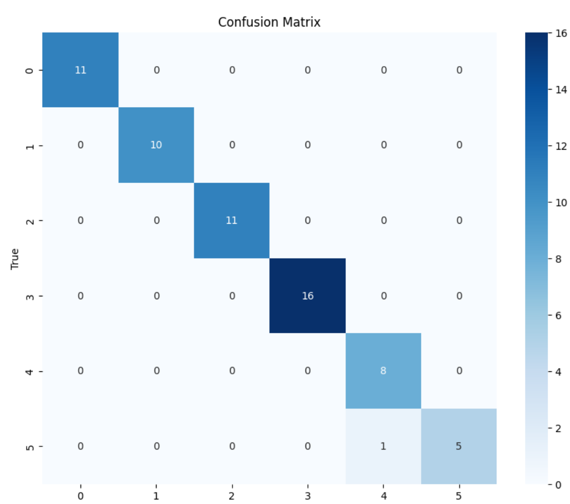

Fig 9- Confusion Matrix.

The XGBoost algorithm was chosen for this research since it is renowned for its ability to handle high-dimensional and heterogeneous data more effectively, which is an imperative need in face recognition systems that are based on the fusion of different features such as Gabor LBP, HOG, and DeepFace, thus resulting in complex, high-dimensional representations. XGBoost is recognized for its ability to effectively handle this type of data without sacrificing valuable information. One of the most important features of XGBoost is that it includes mechanisms to prevent overfitting, making it more reliable than older models such as decision trees or simple clustering models. The algorithm also supports parallelized training. One of the most powerful things about XGBoost is its ability to learn nonlinear feature interactions, which is crucial for picking up on subtle variations in facial features that would be difficult for uncomplicated models to capture. Furthermore, XGBoost provides feature importance scores, which aid in improved interpretation and model analysis, a handy feature for real-world biometric applications. The results of the research showed XGBoost to have the highest classification accuracy among the algorithms of Decision Tree, Random Forest, Gradient Boosting, and LightGBM, which confirmed its superiority and efficiency in this aspect.

The challenges such as different lighting, changing expressions, or different facial angles addressed in image lighting processing, histogram equalization is employed to adjust the lighting distribution to achieve lighting uniformity among images. (Gaussian Blur): We use Gaussian blur to reduce visual noise caused by heavy light or shadows. We use Canny to detect edges so that we can identify important features even with differences in lighting. In order to process dynamic facial expressions and viewing angles, several feature extraction methods are employed, each extracting a type of information. Captures a deep face representation: Deep Face. Sensitive to edges and orientations: HOG. Processes fine texture patterns: LBP. Gabor Filters extract fine details at multiple levels of frequency and orientation. The fusion of these methods enables the system to extract face features even if the angle is altered or the facial expressions are not the same. Finally, but not least, we increase the diversity of the training data by performing operations such as rotation, augmentation, shearing, and horizontal flip. The goal is to simulate different conditions and situations, for the face so the model learns to detect faces in different environments without needing more real images.

9. Conclusion

This study sought to develop a high-performance face recognition system with high accuracy under challenging real-world conditions such as varying lighting, expressions, and viewing angles. To this end, we proposed a whole framework that includes advanced image preprocessing, multi-technique feature extraction, and high-capability machine learning classification using XGBoost. The results, experimented with the CAS-PEAL dataset, show that the combination of DeepFace, HOG, LBP, and Gabor filters—together in one feature vector—significantly improves facial representation. Among the classifiers experimented with, XGBoost yielded the highest accuracy (100%), outperforming Random Forest, LightGBM, and Decision Tree models. The results confirm that the system met its primary objectives: (1) enhancing the quality and diversity of the data via preprocessing and augmentation, (2) rich facial feature extraction using complementary feature extractors, and (3) high accuracy classification via an efficient and scalable learning algorithm. The results show the system's potential for practical deployment in security, surveillance, and real-time authentication systems.

Future work includes optimizing the model for real-time inference, expanding the dataset to include more diverse demographic groups, and integrating the system into edge computing environments for greater scalability and usability.

Acknowledgements

The authors are thankful to Al-Qadisiyah University for their provision of quality resources and learning environment that stimulates research. We appreciate, in particular, the editorial board and referees of the Al-Qadisiyah Journal of Computer Science and Mathematics for the constructive critique and helpful advice.

References

[1] Priyanka, G., & Kumar, J. S. (2022, May). Ensemble learning-based deep neural network model for face recognition. In AIP Conference Proceedings (Vol. 2463, No. 1). AIP Publishing.

[2] Ehab F. Abdel-Kader, Rabab M. Ramadan and Rawya Y. Rizk, "Rotation Invariant Face Recognition Based on Hybrid LPT/DCT Features", International Journal of Electrical and Computer Engineering, Vol. 3, No. 7, pp. 488-493, 2008

[3] Kortli, Y., Jridi, M., Al Falou, A., & Atri, M. (2020). Face recognition systems: A survey. Sensors, 20(2), 342.

[4] Wiskott, L., Fellous, J. M., Krüger, N., & Von Der Malsburg, C. (2022). Face recognition by elastic bunch graph matching. In Intelligent biometric techniques in fingerprint and face recognition (pp. 355-396). Routledge.

[5] Tirkaz, C., & Albayrak, S. (2009, April). Face recognition using active appearance model. In 2009 IEEE 17th Signal Processing and Communications Applications Conference (pp. 940-943). IEEE.

[6] Ali, A. S. O. (2023). Age Invariant Face Recognition using Feature Level Fused Morphometry of Lip-Nose and Periocular Region Features. London Journal of Research In Computer Science and Technology, 23(1), 43-68.

[7] Yasufumi Suzuki and Tadashi Shibata, "IlluminationInvariant Face Identification Using Edge-Based Feature Vectors In Pseudo-2d Hidden Markov Models", In Proceedings of the 14th European Signal Processing Conference, Florence, Italy, 2006

[8] Shermina, "Impact of Locally Linear Regression and Fisher Linear Discriminant Analysis in Pose Invariant Face Recognition", International Journal of Computer Science and Network Security, VOL.10 No.10, pp. 106110, October 2010

[9] Jridi, M.; Napoléon, T.; Alfalou, A. One lens optical correlation: Application to face recognition. Appl. Opt. 2018, 57, 2087–2095.

[10] Napoléon, T.; Alfalou, A. Pose invariant face recognition: 3D model from single photo. Opt. Lasers Eng. 2017, 89, 150–161.

[11] Yang, W.; Wang, S.; Hu, J.; Zheng, G.; Valli, C. A fingerprint and finger-vein based cancelable multi-biometric system. Pattern Recognit. 2018, 78, 242–251.

[12] Patel, N.P.; Kale, A. Optimize Approach to Voice Recognition Using IoT. In Proceedings of the 2018 International Conference on Advances in Communication and Computing Technology (ICACCT), Sangamner, India, 8–9 February 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 251–256.

[13] Wang, Q.; Alfalou, A.; Brosseau, C. New perspectives in face correlation research: A tutorial. Adv. Opt. Photonics 2017, 9, 1–78.

[14] Gowda, H.D.S.; Kumar, G.H.; Imran, M. Multimodal Biometric Recognition System Based on Nonparametric Classifiers. Data Anal. Learn. 2018, 43, 269–278.

[15] Ouerhani, Y.; Jridi, M.; Alfalou, A.; Brosseau, C. Optimized pre-processing input plane GPU implementation of an optical face recognition technique using a segmented phase only composite filter. Opt. Commun. 2013, 289, 33–44.

[16] Mousa Pasandi, M.E. Face, Age and Gender Recognition Using Local Descriptors. Ph.D. Thesis, Université d'Ottawa/University of Ottawa, Ottawa, ON, Canada, 2014.

[17] Khoi, P.; Thien, L.H.; Viet, V.H. Face Retrieval Based on Local Binary Pattern and Its Variants: A Comprehensive Study. Int. J. Adv. Comput. Sci. Appl. 2016, 7, 249–258.

[18] Zeppelzauer, M. Automated detection of elephants in wildlife video. EURASIP J. Image Video Process. 2013, 46, 2013.

[19] Parmar, D.N.; Mehta, B.B. Face recognition methods & applications. arXiv 2014, arXiv:1403.0485.

[20] 3. Vinay, A.; Hebbar, D.; Shekhar, V.S.; Murthy, K.B.; Natarajan, S. Two novel detector-descriptor based approaches for face recognition using sift and surf. Procedia Comput. Sci. 2015, 70, 185–197.

[21] Yang, H.; Wang, X.A. Cascade classifier for face detection. J. Algorithms Comput. Technol. 2016, 10, 187–197.

[22] Viola, P.; Jones, M. Rapid object detection using a boosted cascade of simple features. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Kauai, HI, USA, 8–14 December 2001.

[23] Ouerhani, Y.; Alfalou, A.; Brosseau, C. Road mark recognition using HOG-SVM and correlation. In Optics and Photonics for Information Processing XI; International Society for Optics and Photonics; SPIE: Bellingham, WA, USA, 2017; Volume 10395, p. 103950Q.

[24] Rettkowski, J.; Boutros, A.; Göhringer, D. HW/SW Co-Design of the HOG algorithm on a Xilinx Zynq SoC. J. Parallel Distrib. Comput. 2017, 109, 50–62.

[25] Seo, H.J.; Milanfar, P. Face verification using the lark representation. IEEE Trans. Inf. Forensics Secur. 2011, 6, 1275–1286.

[26] Shah, J.H.; Sharif, M.; Raza, M.; Azeem, A. A Survey: Linear and Nonlinear PCA Based Face Recognition Techniques. Int. Arab J. Inf. Technol. 2013, 10, 536–545.

[27] Du, G.; Su, F.; Cai, A. Face recognition using SURF features. In MIPPR 2009: Pattern Recognition and Computer Vision; International Society for Optics and Photonics; SPIE: Bellingham, WA, USA, 2009; Volume 7496, p. 749628.

[28] Kortli, Y.; Jridi, M.; Al Falou, A.; Atri, M. A novel face detection approach using local binary pattern histogram and support vector machine. In Proceedings of the 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET), Hammamet, Tunisia, 22–25 March 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 28–33.

[29] Xu, X., Wang, X., Sun, Z., & Wang, S. (2021). Face recognition technology based on CNN, XGBoost, model fusion and its application for safety management in power system. In IOP Conference Series: Earth and Environmental Science (Vol. 645, No. 1, p. 012054). IOP Publishing..

[30] Punuri, S. B., Kuanar, S. K., Kolhar, M., Mishra, T. K., Alameen, A., Mohapatra, H., & Mishra, S. R. (2023). Efficient net-XGBoost: an implementation for facial emotion recognition using transfer learning. Mathematics, 11(3), 776.

[31] Ismail, A., Elpeltagy, M., S. Zaki, M., & Eldahshan, K. (2021). A new deep learning-based methodology for video deepfake detection using XGBoost. Sensors, 21(16), 5413.

[32] Nikhil, K. V. S., & Nagalakshmi, T. J. (2023, April). Accuracy Improvement in the Attendance Marking System using Human Face Recognition with Inception Algorithm and Comparing with Light Gradient Boosting Machine (LGBM) Algorithm. In 2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-6). IEEE.

[33] Tien, V. H., & Nam, T. Q. (2024, March). Performance of Hybrid Models with VGG16-XGBoost and VGG16-LightGBM on Fake Face Image Recognition. In The International Conference on Intelligent Systems & Networks (pp. 248-253). Singapore: Springer Nature Singapore.

[34] Gao, W., Cao, B., Shan, S., Chen, X., Zhou, D., Zhang, X., & Zhao, D. (2007). The CAS-PEAL large-scale Chinese face database and baseline evaluations. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 38(1), 149-161.

[35] Ma, R., Chung, S., Kim, S., & Kim, H. (2025). PigFRIS: A Three-Stage Pipeline for Fence Occlusion Segmentation, GAN-Based Pig Face Inpainting, and Efficient Pig Face Recognition. Animals, 15(7), 978.

[36] Cândido, B., Mindala, U., Ebrahimy, H., Zhang, Z., & Kallenbach, R. (2025). Integrating Proximal and Remotensing with Machine Learning for Pasture Biomass Estimation. Sensors, 25(7), 1987.

[37] Akinola, O. A., Olopade, S. O., & Afolabi, A. S. (2021). Development of mobile and desktop applications for a fingerprint-based attendance management system. Indones. J. Electr. Eng. Comput. Sci, 24(1), 570-580.