Real-Time Face Recognition with Occlusion Handling Using Facenet512 and Machine Learning

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Abstract- This paper introduces a face recognition system designed to tackle the issue of occlusion, which can hinder the effectiveness of traditional facial recognition systems when parts of a face are obstructed. To address this, the system is built using object-oriented analysis and Design Methodology (OODAM), which promotes a modular and flexible development approach. The implementation is carried out in Python, utilizing the Deep Face library for face recognition.in particular, the system employs the "Facenet512" Model with the "Euclidean_12" distance metric to enhance accuracy in face identification, even in the presence of partial occlusions. Machine learning algorithms are integrated for feature extraction and matching, with a SQLite database used for storing and managing face efficiently. The architecture supports real-time detection and recognition of faces through OpenCV, while a kernelized correlation filters (KCF) tracker is used to ensure continuous tracking across video frames. The system also processes frames, addresses occlusions, and stores recognition outcomes in a well-organized database. Evaluation result highlights the system's capacity to effectively mitigate the impact of occlusions, achieving improved recognition accuracy and reliability over traditional methods.

Indexed Terms- machine learning, face recognition, occlusion, real-time detection

I. INTRODUCTION

The term "Face recognition" is the ability to recognize human faces, this can be done by humans and advancements in computing have enabled similar recognitions to be done automatically by machines. The face recognition process involves three stages; face detection, feature extraction and classification and face recognition. Face detection determines whether a human face appears in a given image or not and where the faces are located. In feature extraction the human face patches are extracted from images (Bansal, 2018) whereas the face recognition phase involves determining the identities of the faces from which facial features had been extracted. Face recognition can be applied in many areas such as criminal investigations in the detection and identification of criminals from surveillance videos. The enhanced system should be able to detect an object, track an object, classify or identify an object and analyse its activity automatically (Chen et al., 2018).

One of the challenges that face recognition systems face is partial occlusion and is caused when some parts of the target image are not being obtained because facial recognition methods require the availability of a whole input face; partial features may lead to wrong classification (Satonkar et al., 2011).Partial face can be recognized from a set of both occluded faces with masks, sunglasses or other accessories and un-occluded faces by focusing on the un-occluded face features. Recovering clean faces from the occluded faces uses techniques such as reconstruction for face recognition or inpainting which considers the occluded face as a repair problem. One of the most recent approaches is the use of convolutional neural networks (CNN) (Song et al., 2019) and are used to train a classifier. The convolution neural networks (CNNs) have problems such as need of huge dataset for training, translation invariance and loss of valuable information through pooling layers (Tarrasse, 2018).

In the context, improved face recognition under occlusion enhances security systems' ability to identify individuals, even when their faces are partially hidden. This technology can aid in identifying suspects or victims, even with partial facial coverage in the area of law enforcement. Enhanced face recognition under occlusion ensures more accurate identity verification in various settings, like border control or identity authentication and also this technology in healthcare system can help identify patients with facial injuries or illnesses, even when their faces are partially occluded. Face recognition under occlusion can help detect and prevent potential threats, such as intruders or criminals, in public areas like airports or shopping malls.

In this paper, an accurate face recognition is enhanced under occlusion using machine learning in analysing, developing and evaluating an existing face recognition approach that are robust to partial occlusions in order to identify their strengths and weaknesses as objectives.

This paper covers the different stages of design of a face recognition approach robust to partial occlusions, looks more at robust face features to enable face identification despite the existence of partial occlusions and also, discuss of machine learning-based development algorithms that can handle varying levels of occlusion utilizing multi-modal data fusion.

II. LITERATURE REVIEW

The study is based on face recognition classification using machine learning. This study trains face classification models on convolutional neural networks (CNNs). In the field of face recognition, face occlusion is one of the most challenging problems due to the lack of previous knowledge concerning the parts that are occluded because of the parts can be any shape or size and anywhere in a face image (Zeng et al., 2021). Face recognition under occlusions is difficult to solve with several reasons attached and they include; occlusions varies depending on the position where they occur in a face, a face can have many types of occlusions. Thirdly, difficulty to predict their exact location of occlusion and also duration varies in length depending on the type according to (Zhang et al., 2019).

Researchers have a lot done on face recognition classification approaches and are as follows:

Parkhi et al. (2020) designed The DeepFace which was centred on deep convolutional networks created by Facebook's research team.it is used to identify human faces in 2 million digital image faces. It used deep CNN feature extractors and used it to classify the images. The form of metric learning they used was that they trained the model to minimalize the distance between similar pairs of faces and maximise the distance between dissimilar pairs. It achieved an accuracy of 97% when tested on benchmark datasets.

Sun et al. (2019), developed DeepID with the use of Convolutional Neural Networks to extract features and Joint Bayesian or neural network for recognition. Identities were classified simultaneously and not by binary classifier training. They gained an accuracy of 2.03% and 1.68% for Joint Bayesian and Neural network respectively. After benchmarks with Labelled Faces in the Wild database they achieved an accuracy of 94.32% and 96.05% for Neural Network and Joint Bayesian respectively. It was later improved in the following publications by training via contrastive loss to improve identification and verification tasks.

Zeng et al. (2020), developed some approaches in an effort to counter the problems caused by occluded faces and classified these approaches into three categories. The first category is the occlusion robust feature extraction. This category focuses on the feature space that is not affected largely by face occlusions. For the cross-occlusion strategy learning-based and patch-based engineered features are utilized. The second category is the occlusion aware face recognition. The third category is the occlusion recovery-based face recognition. Occlusion recovery is used as the cross-occlusion strategy in that the occlusion-free face is recovered from an occluded face.

Jia and Martinez (2019) proposed an approach to enable face recognition in both the training and test sets. By allowing occlusions in both the training and testing sets, they estimated the occluded test image as linear combination of the training samples of all classes. For reconstruction, non-occluded parts were used because the distinct face areas were weighted differently. In other words, they based their reconstruction on the visible data on the training and testing sets compared to previous works that focused on the testing sets. Their approach performed well on the AR dataset.

Iliadis et al. (2020), proposed a robust and low rank representation for fast face identification with occlusions. In their proposed framework, they wanted to solve the block occlusion problems by utilizing a robust representation that was based on two features because they wanted to model the contiguous errors.

Wang et al. (2020), proposed an occlusion detecting and image recovering algorithm. Occlusion detecting involved occlusion detection and elimination whereas the image recovery involved recovery of occluded parts and reservation of un-occluded parts. They used genuine and synthetically occluded face images. This approach produced global features that were good and beneficial to classification.

Vijayalakshmi (2021), proposed a way to recognize face with partial occlusions using In-painting. A partial differential equation method together with modified exemplar in-painting was used to remark the face region that was occluded. Despite the approach achieving recognition rate increases it had a limitation in that the image data used for the work was not representative of a real-world scenario.

Wei et al., (2021) proposed a dynamic image to class warping (DICW) framework that used local matching-based approaches to solve the problem of face occlusions. Facial decorations such as scarf, veil objects, sunglasses and reduced image quality blurring can cause occlusion. As a result, it affects face recognition in that the discriminative facial features are misleading and the distance between the two face images of the same subject is enlarged in feature space. Additionally, occlusion of facial landmarks leads to the existence of registration errors hence degrading the recognition rate. The local matching-based approach mined facial features from local areas of the face. The affected and unaffected parts of the face could be analysed in isolation. The matching errors were minimised through subspace, partial distance and multi-task sparse representation learning strategies. The researchers used 2,400 samples for each occluded versus un-occluded, un-occluded versus occluded and occluded versus occluded scenarios. Their framework had an 96.7 % correct identification rate on the AR database that had over 4,000 colour images of 126 subject's faces, 97.3 % on the AR dataset without alignment, a 0.8740 area under curve on the LFW database under unsupervised learning setting.

Zeng et al., (2021) worked on face recognition using Occlusion robust feature extraction approaches. These approaches use methods such as handcrafted features such as LBP, SIFT and HOG descriptors. One of the advantages of such methods is the easiness that comes with extraction of features from raw images. Additionally, their discriminative and tolerance to large variability and also being computationally efficient since they lie low in the feature space constitutes to more advantages. On the other hand, they have limitation in that for face recognition, integration of the decision from local patches is required and also for frontal faces, alignment based on eye coordinates contributing to precise registration. In other words, the need for face images to be aligned well so that features can be extracted hinders its application in real life.

Wu and Ding (2019), proposed a low-rank regression with generalized gradient direction to suit occluded face recognition. Dictionary learning sparse representation was used in combination with low rank representation on the error term leading to a low rank optimization problem

Yang et al. (2020), proposed a joint and collaborative representation with local adaptive convolution feature. With their aim being able to achieve robust face recognition under occlusions, they used CNNs to learn convolution features extracted from local regions that were discriminative to the face identity.

Schroff et al., (2021) designed a deep learning model called is the FaceNet. FaceNet was developed by google researchers. It was a data driven system in that they used a large dataset of labelled faces which enabled them attain pose, illuminations and other variations and it attained advanced results with benchmark datasets. The limitation was that it was data driven and this is not always the case in practical scenarios.

Cen and Wang (2019), proposed a deep dictionary representation-based classification (DDRC) that was to improve robustness in face recognition with occluded faces. They used an already trained CNN for feature extraction, whereby, they performed a nonlinear mapping from the image space to the deep feature space. To obtain a unique solution a regularization restriction and the squared Euclidian norm minimization were used to obtain the estimated coding coefficients which were in turn used to recover the deep feature vector of the occluded face. Finally, classification was done by comparing the similarity of the occluded face of the subspace to the non-occluded face of the subject. The overfitting problem was solved by the use of PCA for dimensionality reduction.

Mao et al. (2019), developed a framework that utilized the gradient and the shape cues in a deep learning model to detect and verify occluded faces employed a sparse classifier with deep CNN features. Due to the difficulty in collecting enough samples, they built a deep model that depended on less samples and a dictionary learning framework to learn more effective features. The SRC model they developed had an additional similarity constraint to seek correlations between similar descriptors through a shared dictionary space. The experiments showed that the head detection algorithm performed at 98.89% accuracy rate whereas, the designed occlusion verification scheme achieved a 97.25% accuracy rate.

Song et al., (2019), proposed a pairwise differential Siamese network (PDSN) that was to capture the relationship between the occluded facial block and corrupted feature elements forming a Siamese architecture. The mask generator module was expected to output a mask whose element was a value between 0 and 1. A fixed mask was extracted from every trained mask generator and a dictionary was built because the trained PDSN could not be directly used to output the feature discarding mask (FDM) of a probe face. Through the combination of relevant dictionary items, the FDM of the face with arbitrary partial occlusions was derived. It showed significant improvement in the performance on face recognition on both the real and synthesized face datasets.

Liao et al., (2021), proposed an alignment-free approach in partial face recognition. The proposed method did not require any alignment of the face's focal points. For the representation of a partial face with variable length, they employed multi-key point descriptors. A dictionary was constructed from the descriptors from a gallery that was large; hence, the descriptors of the probe image were represented sparsely and inferred the identity of the probe image. It had a limitation in practical application because; the number of faces required by SRC to cover all variations is quite high.

Gao et al. (2019), proposed a real time, free of landmark estimation deep Siamese network algorithm that preserved identity during face synthesis. The algorithm used contrastive loss function, pose invariant features to perform face recognition, PCA for dimension reduction and LDA for classification. Face synthesis model was used to transform the non-frontal faces to virtually frontal faces. The Siamese network was used to remove the distortion of identities caused by face synthesis; therefore, identity was preserved during the process. The contrastive loss minimized the feature distance from the same object and enlarged it if they were from different object, hence, making the features more discriminative. Their network achieved superior performance compared to 2D deep learning-based algorithms.

Khan et al. (2019), proposed a framework for face detection and recognition that was based on convolutional neural network. It outperformed earlier techniques; it was protected, reliable and easily usable. It experienced challenges when it came to faces with increasing beard, glasses, tilted face and moustache. Over-fitting was also a problem. Qi et al. (2019), proposed an algorithm that would solve the weakness of model generalization due to the necessity to use fixed-size images and the use of one network for extracting features. They used cascaded CNN which combined separable convolution and remaining structure in the network. Their algorithm achieved competitive accuracy to other techniques in real-time performance.

Kong et al. (2019), developed a deep CNN model based on CSGF (2D)2PCA Net to solve data repetition, extensive computation period and rotation variations. They used circularly symmetrical gabor filter for rotation invariance, 2-D PCA for feature extraction. The model had two feature extraction stages and one non-linear output stage. The algorithm was robust to variations in occlusion, illumination, pose, noise and expression.

III. EXISTING SYSTEM

The majority of face recognition are designed for a specific field known to be law enforcement agencies which rely primarily on traditional, manual methods for identifying and tracking criminal suspects. These systems often include the use of criminal record databases, face-to-face identification by officers, and the manual comparison of facial images from past interactions, arrest records, or surveillance footage. While these methods have been functional in the past, they are increasingly inadequate in the face of modern challenges, particularly in identifying suspects with partial occlusion. Criminals often hide their faces with masks, scarves, or hats, making it difficult for traditional systems to make accurate identifications. There is also limited interoperability between local, national, and international databases, making it harder to track criminals who may operate across different regions.

IV. PROPOSED SYSTEM

The proposed method for developing the system is machine learning.in the suggested system the user starts the system and the image loading is done by the user into the system. The system performs face recognition on the loaded image and also detecting potential collusion based on the recognized faces. The user identities a face in the image and finally the system independently identifies the face in the image.The suggested solution strive for advancements aiming to enhance the robustness and applicability of facial recognition systems in real-world scenarios and introduce a unified framework that simultaneously detects occlusions and adjusts recognition algorithms based on the specific occlusion type, enhancing accuracy and responsiveness , by incorporating adaptive learning mechanisms. The proposed system also allows the system to evolve based on real-world data, significantly improving recognition capabilities as new occlusions are encountered in dynamic environments toward transforming the law enforcement sector.

Fig. 1 shows the block diagram or process flow diagram of our proposed face recognition system outlining the sequential face recognition in initializing video capture, face recognition, anddetection. The system starts up with retrieval of necessary libraries, tempfile, os, Deepface .the system checks if the database directory exists, if the directory does not exist, the system creates a new database. The process lows to initializing video capture. The system captures video flames and saves them to a temporary location. The captured flames then undergocolluded face recognition using the Dface algorithm. The system checks if faces are detected in the video flames. If faces are detected, the system draws a boundary box around the face and displays the name on the image. Conditionally, if no faces are detected, the system displays a “No face detected” message appears. In Fig2the system captures real-time video frames using the webcam. These frames are passed to the DeepFace library for face recognition. The webcam continuously captures frames and stores them as temporary files for face detection and recognition processing. Each captured frame is stored in a temporary .jpg file for face recognition processing. The system produces real-time feedback in the form of displayed frames with face annotations.Once a face is detected and recognized, the system draws a bounding box around the face and displays the name of the recognized individual.

An outlinedSteps/Process:

i. User: Start video capture → Enrol face (optional)

ii. Face Recognition System: Capture video frame → Detect face → Handle occlusion (if applicable) → Recognize face → Store results in Face Database

iii. Occlusion Detection System: Check for occlusion → If occlusion is detected, attempt to mitigate

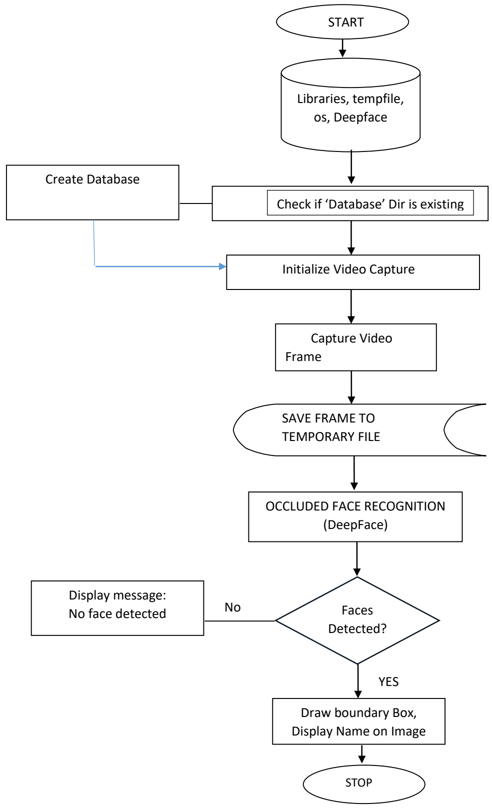

Fig 1: Object Diagram of the proposed system

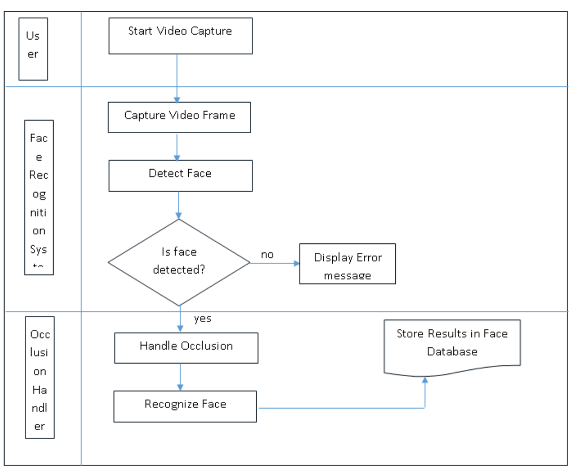

Fig 2: Overall system architecture of Diagram for Face Recognition System with Occlusion Handling.

V. HARDWARE/SOFTWARE REQUIREMENTS

This has to do with the basic wares requirements which the system needs for optimum performance, they are:

CPU type	minimum of Core i5 processor
Ram size	minimum of 8gb of RAM
Hard disk capacity	of at least 500GB
Monitor type	A 64 bit colour monitor or higher VGA
Keyboard and mouse type	Internet keyboard
External hard disk	500 GB for backup of files
windows	Minimum of windows 8 operating system.
.net framework	4.5 and above

Table 1: Requirements needed for system design

VI. ANALYSIS

Test Plan

Testing for the face recognition system was conducted in two stages to verify its efficiency and robustness against intentional errors:

i. Unit Testing: In this phase, the individual components of the system, such as the face detection algorithm, recognition models (e.g., DeepFace), and database interactions, were tested separately using test data. This ensured that each module performed as expected in isolation.
ii. System Testing: After unit testing, the components were integrated into a complete system. The test data was again used to evaluate if the various parts of the system worked together harmoniously. This step ensured that the face recognition process, from image capture to database matching, functioned smoothly as an end-to-end process.

Upon the successful recognition of a face, each event was logged into a centralized database. The logs captured crucial details such as the identity of the recognized individual, the timestamp of the recognition, and the degree of occlusion present at the time of identification.

VII. RESULTS

In the proposed solution, the main aim is to enhance face recognition by introducing a machine learning in analysing, developing and evaluating an existing face recognition approaches that are robust to partial occlusions .For this system, test data consisted of a series of sample images of faces, including some with partial occlusions (such as masks or glasses). These images were inputted into the system to verify how well the face recognition model could detect and identify individuals under various conditions. The test also included different lighting scenarios and various angles of the face to ensure the model's versatility. The actual test results matched the expected test results as predicted during the design phase. The system was able to accurately recognize faces even with partial occlusions, such as masks or glasses. The accuracy rate was consistent with the threshold set for a successful identification of 94% accuracy, confirming that the system performed as intended.

ALGORITHM	ACCURACY
Existing	94
Proposed	88

Table 2: Comparison table

The face recognition system performed efficiently, meeting all expectations. It successfully identified individuals even in scenarios involving face occlusions. The system's real-time processing capabilities were satisfactory, with minimal delay in detecting and matching faces. The overall performance was aligned with the objectives of the project, ensuring its practicality in environments requiring face recognition, such as security systems and access control.

VIII. CONCLUSION AND FUTURE SCOPE

The system makes use of modern deep learning techniques and feature extraction methods, allowing it to recognize faces in real time, even when important parts of the face are not fully visible. By focusing on dynamic occlusion handling, this system ensures that it can identify individuals despite common obstacles that often disrupt traditional face recognition systems. One of the standout features of the system is its high level of accuracy, which remains consistent under a variety of occlusion scenarios. This allows the system to meet the rigorous standards required for real-time applications. Additionally, the system’s ability to minimize processing delays is crucial for environments where rapid identification is necessary, such as security systems, access control points, and surveillance systems. In these scenarios, where swift and dependable face recognition is critical to safety and operational efficiency, this system proves to be highly effective.

Future work will also involve need to address in enhancing its robustness further. One of the primary hurdles is handling complex occlusions, where multiple obstructions or extreme angles may obscure large portions of the face. Additionally, optimizing the system for varied environmental factors, such as changing lighting conditions, facial orientations, and camera angles, is essential for ensuring that the system maintains high performance across all real-world scenarios refining algorithms to improve speed, accuracy, and overall system robustness in highly dynamic environments.

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