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An Experimental Study of Facial Recognition Performance for Real-Time UAV Surveillance in Urban Environments

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Abstract:

In today's era, facial recognition is common in every aspect of life, whether in smartphones, security, attendance management, healthcare, or law enforcement. Modern facial recognition uses a camera mounted in different locations in urban environments but is unable to move if a suspect is hidden in locations where the mounted camera can't trace easily. Therefore, we need to use a moving object equipped with a camera and sensors to monitor suspects wherever they are present in the urban vicinity. To solve this problem, this experimental study proposes optimizing the performance of facial recognition parameters for real-time suspect detection through drone imaging and face recognition algorithms in urban environments. To achieve this, the Unmanned Aerial Vehicle is equipped with a high-definition camera and sensors, allowing it to fly in predefined urban locations and capture images to find the suspected individual through the image processing technique Convolutional Neural Networks (CNNs). In this research, the performances of three facial recognition systems, Local Binary Pattern Histogram (LBPH), FaceNet, and Face Recognition, have been presented for Frames Per Second, Accuracy, and real-time tracking. A comparative analysis of the proposed work is also presented to validate the study, where a minimum confidence threshold of 80% is achieved.

Keywords: *Urban surveillance, face detection, Unmanned Aerial Vehicle, and Artificial Intelligence.*

I. INTRODUCTION

Real-time face recognition technology on Unmanned Aerial Vehicles (UAVs) is becoming a game-changer for improving urban surveillance and safety. Real-time monitoring and identification of people in intricate urban settings is made possible by the combination of UAVs with cutting-edge image processing algorithms like Convolutional Neural Networks (CNNs), Local Binary Pattern Histogram (LBPH), Face_Recognition, and FaceNet. The limitations of traditional surveillance systems, such as static monitoring, restricted coverage, and accessibility issues, can be effectively addressed by analyzing a few of these algorithms. Facial recognition systems may function efficiently across wide regions by utilizing UAV mobility and high-resolution imagery, giving security and law enforcement organizations useful information [1-5]. Even if new technology promises to increase accuracy and efficiency, problems, including recognition in different lighting situations, distances, and angles, still exist. Concerns about privacy and ethics surrounding UAV-based surveillance also emphasize the necessity of responsible deployment and compliance with the legal framework. By introducing a thorough UAV-based real-time face recognition system, assessing its effectiveness in various scenarios, and providing insights into its useful applications for urban security, this work fills these gaps. [6-9].

The streets in Karachi are not safe, and criminal activities are higher than in any other city in Pakistan; therefore, urban safety and surveillance through drones are in need. In some areas, the security personnel are unable to reach due to various hurdles therefore this concept is more suitable for them to operate in such areas and monitor the security of public safety. When we talk about the United Nations' sustainable goals, this research project will cover SDG 11 to make cities safer for everyone, as well as its real-time monitoring to improve law enforcement, which covers SDG 16, promoting peace, justice, and strong institutions [10].

Facial recognition is evolving day by day due to its importance and variations in data, but CNN has made it easier to understand and implement in every aspect of life with various combinatorial algorithm approaches in the research world. The main focus of this research project is to implement facial recognition algorithms to the real-time data coming from drone imaging to detect the suspected one and inform the concerned authorities [11].

Variability in facial appearance due to many elements, such as obstructions, position variations, facial emotions, and lighting changes, is one of the main challenges. These elements have the potential to greatly affect facial recognition systems' performance, resulting in mistakes and inaccuracies. Accurate face recognition is further complicated by the existence of noise and imperfections in images. Furthermore, the security and dependability of face recognition systems depend on their capacity to deal with spoofing attacks, in which attackers try to trick the system by utilizing modified or fake facial images [12-14]. The necessity of creating strong legal frameworks and moral standards that regulate the use of such technologies is highlighted by issues with data security, consent, and the abuse of surveillance capabilities. Ensuring the responsible and ethical distribution of these technologies will involve interdisciplinary teamwork and vigorous stakeholder contribution. [15].

The main objective of this article is to study the facial recognition variation parameters like distance and angles while monitoring UAVs in urban environments. To elevate the status of this work further, we'll make efforts to transform it into an Autonomous UAV by using any suitable microcontroller. The network established between the computer and the UAV is capable of two-way communication. The drone can stream a live video feed to the computer, where analysis is performed, and the computer can send instructions to the drone that dictate its movement, all in real-time. This implies that it would function on its own, detect, and then track the locked target.

The following sections are based on previous work done in this domain followed by the problem formulation and its proposed solution. In section IV, methodologies and applied techniques are discussed, while experimental analysis is given in section V. The Final section presents the conclusion of the study.

II. RELATED WORK

The concept of facial recognition began to emerge as a topic of discussion and research in the mid-20th century [16], primarily driven by advancements in computer vision and pattern recognition. Early talks on facial recognition date back to the 1960s and 1970s, when researchers explored the feasibility of automating the process of identifying and classifying faces using computational methods [17]. However, it wasn't until the late 20th and early 21st centuries that significant strides were made in developing practical facial recognition systems. Recently, drones have turned somewhat into a buzzword as the excitement around drones is ever-growing, and the associated costs seem to be decreasing. Due to this ease of access, many people have been able to research and implement computer vision-related projects while utilizing drones [18]. Figure 1 presents real-time drone-based facial recognition mobility over Seaview, Karachi, Pakistan.

Figure 1: Real-time Facial Recognition in Urban Environments [7].

In recent years, significant improvements have been made in facial recognition models, processed by progression in the field of deep learning and computer vision with data processing techniques [11]. One notable improvement is the enhanced accuracy and robustness of facial recognition algorithms, achieved through the evolution of more urbane neural network architectures and training methodologies. Deep learning models, particularly convolutional neural networks (CNNs) [5], have demonstrated remarkable performance in extracting discriminative features from facial images, enabling more accurate identification and verification of individuals across diverse conditions such as varying illumination, facial expressions, and occlusions. Researchers at the Institute of Information Science, Academia Sinica were able to create a facial recognition system that uses drones. They implemented two facial recognition systems, Face++ and ReKognition, and then used them to conduct empirical tests to evaluate the efficacy of drone facial recognition considering factors that may affect performance such as distance from a subject, angle of depression, and drone height. Distance, angle of depression, and height all refer to the drone position [19-20].

The review table below summarizes recent advancements in UAV-based real-time facial recognition for urban safety and surveillance, highlighting significant contributions, techniques, and limitations from studies conducted between 2019 and 2024. Key contributions across these studies involve enhancing accuracy, reducing latency, and addressing privacy concerns in real-time applications. Techniques such as convolutional neural networks (CNN), VGG-Face, FaceNet, LBPH, and edge computing were commonly utilized, offering robust options for facial recognition and anomaly detection. Many studies explored path optimization, ethical frameworks, and AI-powered threat detection to create safer, more responsive surveillance systems. However, limitations persist, including accuracy drop-offs at higher altitudes and in low-light conditions, high computational and implementation costs, and challenges with network dependency and ethical compliance. Collectively, these studies underscore the potential of UAV-based facial recognition systems for urban security while underscoring the need for continued research on ethical deployment, privacy considerations, and technological improvements to overcome environmental and infrastructural limitations.

Table 1: Key contributions from recent studies and the typical challenges faced.

Reference	**Authors & Year**	**Contribution**	**Technique**	**Limitations**
[21]	Smith, R., Wang, L., & Thomas, P. (2019)	Explored the effectiveness of UAV-based real-time facial recognition in urban areas	CNN model, off-drone data processing	Limited to low-altitude flights due to reduced accuracy at high altitudes
[22]	Garcia, M., & Lopez, R. (2020)	Focused on reducing latency in UAV-based surveillance systems	Edge computing and deep learning integration	Network dependency affects performance during disconnection
[23]	Li, J., & Zhang, Q. (2020)	Studied the effectiveness of MTCNN and FaceNet for real-time surveillance	MTCNN and FaceNet for facial recognition within 1.5m	Significant accuracy drops beyond short-range detection
[24]	Chen, S., Han, Y., & Park, J. (2021)	Enhanced UAV autonomy for optimized path planning in surveillance	Path optimization combined with facial recognition	Ethical concerns in automated tracking raised by public
[25]	Patel, A., & Singh, H. (2021)	Addressed privacy and ethical challenges in UAV facial recognition	Ethical framework proposal for data use in surveillance	Lack of technological solutions to enforce privacy guidelines
[26]	Wilson, K., & Lee, J. (2022)	Compared facial recognition accuracy between CNN and VGG-Face for UAVs	VGG-Face model implementation, with CNN benchmark	Accuracy is impacted by environmental factors like lighting and distance
[27]	Nguyen, V., & Tran, D. (2023)	Developed multi-target facial recognition for crowded urban settings	Real-time multi-face tracking using YOLO-Face	Reduced accuracy in densely populated environments
[28]	Ahmed, M., Chen, Y., & Roberts, T. (2023)	Analyzed real-world performance of FaceNet and LBPH in urban settings	LBPH and FaceNet models, tested in variable lighting	Susceptible to reduced performance under poor lighting and occlusion
[29]	Sharma, T., & Rao, K. (2024)	Examined ethical implications and public perception of UAV facial recognition systems	Social impact surveys and ethical scoring system	Lack of clear guidelines for balancing surveillance effectiveness with public trust
[30]	Brown, E., & Shaw, T. (2024)	Reduced data latency in UAV surveillance with edge computing	Edge computing for real-time facial recognition	High implementation costs and reliance on stable network infrastructure

The literature review highlights how rapidly face recognition technologies are developing, but the more technical study of algorithms like CNNs, LBPH, and FaceNet is required to put their advantages and disadvantages in UAV-based applications into perspective. For example, LBPH offers robustness at reduced computational costs, but it suffers from extreme viewpoints and lighting variations, whereas CNNs are excellent at feature extraction but require a lot of processing resources. The comparative tables in the result section provided performance measures like accuracy over various distances and angles. Clarity would also be improved by visual aids, such as chronologies of technological advancements and how they have been incorporated into UAV systems. Furthermore, it is necessary to critically examine the ethical complications, which include privacy issues, possible abuses of monitoring, and social effects. A balanced viewpoint will be provided by incorporating frameworks such as GDPR or ethical guidelines suggested for AI technologies, guaranteeing the appropriate use of UAV-based facial recognition in urban surroundings.

III. PROBLEM STATEMENT AND ITS PROPOSED SOLUTION

A. Problem Description

The streets of Karachi city are riddled with theft and crime that compromise peace and a safe place to live for the people. Thus, we aim to utilize Unmanned Aerial Vehicles (UAVs) specifically designed with facial recognition tools to help mitigate this problem. The objective will be to create an efficient and effective way of identifying, and also tracking in real-time people creating or attempting to commit a crime stopping theft in its tracks while orderly enforcing laws. The main issue may be occurred for the face detection by drone is the distance and angle of measures in populated area as stated by Figure 2.

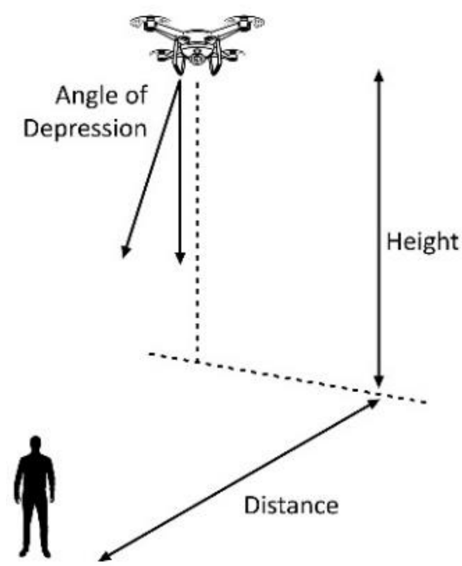

Figure 2: UAV Surveillance Geometry for Facial Recognition [17]..

B. Solution Framework

A face recognition system based on UAVs can be proposed to detect and follow suspects to reduce urban crime and improve public safety. The system would combine high-resolution cameras, real-time tracking, and facial recognition algorithms. By comparing real-time images with a secure criminal database, the drones would recognize people, monitor pre-designated regions, and autonomously traverse crime hotspots. The facial recognition model must have a minimal confidence level to assure appropriate identification and be sensitive to variations in brightness, angles, and distances. The real-time monitoring of the suspected image will be monitored through the combination of UAV and state-of-the-art path-planning algorithms attached with the processing system and if the target is found after verification it will be sent to law enforcement instantly.

The workflow presented in Figure 3 is the proposed solution for real-time facial recognition through drone imagery. Initially, the process starts with communication of drone and ground system (PC/Laptop) and drone stats to send video to the system. The system will video process in real-time with a millisecond time frame and find suspected one through an image processing technique. The proposed solution also maintains the safeguards of people's privacy using standard regulations. The public will be informed earlier about the operation and media, or information will be displayed through media banners about the monitoring.

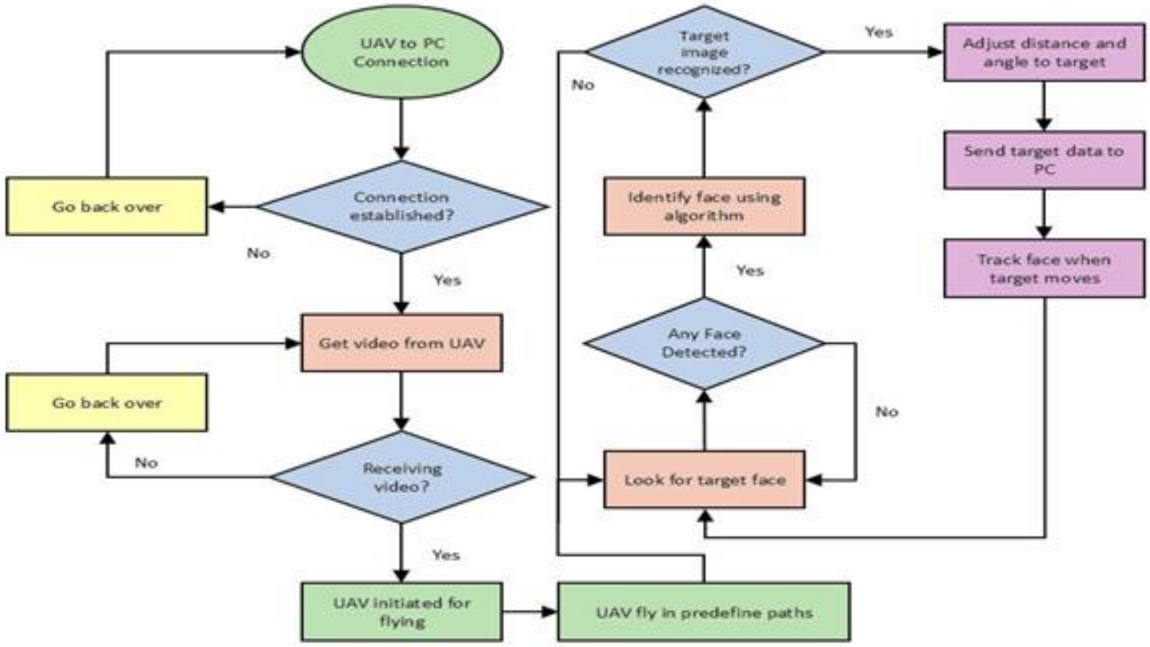

Figure 3: Workflow Diagram for UAV-Based Facial Recognition System

IV. Methodologies and Techniques

In this section, the proposed methodology will be defined for real-time implementation of facial recognition through the use of a camera-mounted UAV. The process involves drone imaging, data transmission, video processing, and facial recognition for the smooth conduction of the process without delays, which is the main requirement in this study. Each step is followed with the highest possible accuracy and efficiency so that it can be used in future applications. Following are the series of steps involved in our proposed methodology.

A. Data Collection and Preparation

a. *Training and Testing Data for Facial Recognition:* The main requirement of this study is to capture high-quality imaging and its management with facial-related features like distance, pose, angle, quality, and facial expressions. In this study, sample data is collected directly from an HD camera with different distances, angles, lighting, and other factors. After data collection, its augmentation is required to rotate, scale, and flip where necessary. The next step is to categorize the data into test and training datasets with a ratio of 20/80, which requires training the model for the detection of suspected images.

b. *Database Configuration and Encoding Storage:* MySQL database management is used to configure the dataset and its storage, where the face encodings will be saved with a unique facial feature and metadata. Additionally, Create, Read, Update, and Delete (CRUD) operations will be used for data management in the database. However, some common facial recognition models, i.e., FaceNet, will be used for required face encodings necessary for fast retrieval and face matching in real time.

B. Face Recognition Process

a. *Image Processing Workflow:* Now for the face recognition process, initially, the UAV sends video data in real-time to the ground system where video frames will be processed, i.e., resizing and RBG color space for efficient processing. To counter lighting conditions, an image enhancement technique called histogram equalization may be used to improve image visibility. Finally, the CNN algorithm will be applied to identify the region of interest, with the data of faces filtered through processed images and sent to the system to identify the suspected image.

b. *Real-Time Face Detection and Tracking Mechanism:* In real-time face detection and tracking, detected faces are compared against a database of stored face encodings. Upon a successful match, the system retrieves relevant information associated with the identified individual. For tracking the face encodings, the Kanade–Lucas–Tomasi (KLT) feature tracker is incorporated to continuously track suspected individuals within the camera frame. Once tracking is confirmed with the suspected person, official authorities will be informed.

C. System Integration and Testing

a. *Integration of Hardware and Software Components:* The integration of hardware components, including the camera, flight controller, GPS, and sensors, with software elements such as facial recognition algorithms, database management, and communication protocols ensures seamless operation of the UAV-based facial recognition system. The physical layout of the quadcopter drone is shown in Figure 4, along with technical specifications shown in Table 2. Robust communication protocols have been used to provide smooth communication between UAVs and ground stations. Additionally, power and processing resources are optimized to maintain a balance between battery life and processing demands, ensuring prolonged flight times and effective performance in real-time recognition tasks.

b. *Testing in Controlled Environments:* The system undergoes extensive testing in both simulated and real-world environments to ensure its reliability and effectiveness. Initially, the dataset is created as a sample subject by four students, Mahad, Bilal, Araib, and Asghar, with their names, ages, and locations in a controlled environment (Laboratory). All data has been marked with labels for identification through image processing. For algorithm designing CNN with three standard facial recognition systems, LBPH, FaceNet, and Face_Recognition system have been used for face identification. The testing mainly depends upon the variation of distance and angle of depression with a high-definition camera along with lightning variations. Moreover, the UAV system is tested with various flight paths, obstacle configurations, and lighting conditions, allowing for fine-tuning of algorithms designed in controlled settings.

Figure 4: Custom F450 Quadcopter System with Remote Controller [31]

Technical specifications of Custom F450 Quadcopter System with Remote Controller are given in Table 2.

Table 2: Technical Specifications F450 Quadcopter

Specification	Details
Frame Type	F450 Quadcopter Frame (DJI Flame Wheel)
Dimensions	Diagonal Wheelbase: 450 mm
Weight	~282 grams (without motors, ESC, or battery)
Material	Glass fiber and nylon composite
Motor Compatibility	22×12 mm brushless motors (e.g., 2212 KV920 or KV1000)
Propellers	10x4.5 or 9x4.5, inch propellers (plastic or carbon fiber)
Flight Controller	Compatible with APM, Pixhawk, DJI Naza-M V2,
Electronic Speed Controllers (ESCs)	30A ESCs (recommended)
Battery	3S or 4S LiPo (11.1V or 14.8V)
Payload Capacity	~800-1000 grams (including camera, gimbal, and accessories)
Maximum Flight Time	10-15 minutes (depending on payload and battery capacity)
Maximum Takeoff Weight	~1600 grams
Recommended Motors	2212/920KV brushless motors
Mounting Accessories	Gimbal, camera mount, and sensor integration options
Flight Speed	Up to 15 m/s (depending on setup)
Connectivity	Supports telemetry via 2.4 GHz or 5.8 GHz communication modules

V. Experimental Results and Analysis

To validate the work, the experiment was done in the project lab with four different students' faces. Parameters like FPS, Varying distances, and varying angles have been considered for successful implementation of the proposed system. After initial testing at the lab, the system was integrated into UAV for real-time facial recognition in an open environment like the university's ground.

A. Frame Per Second (FPS) Distribution Test

The first test was used to measure the FPS so that each system could analyze real-time efficiency. FPS can be useful in the measurement of the performance of a system; the more FPS can be analyzed then the more optimized the system is. The system that is analyzing a high amount of FPS might have low accuracy as it isn't doing enough analysis on each frame. This measure is extremely important to our system because there is a target to track. If the system runs too slowly then the target could already be long gone while the system is still analyzing old frames. This test was done by taking the time when a new frame came into the system and again taking the time when the system was done analyzing that frame. The start time is then subtracted from the end time giving us how long it took to process the frame. By repeating this process for each frame, we can then figure out how many frames are being analyzed per second. This test was done with zero to two people in the frame to see what kind of effect multiple people would have on the system's performance.

The face detection system was applied to four different faces with varying background and foreground effects as given in Figure 5, maintaining a steady frame rate of 20 FPS. Each individual's details, including their name, age, and location, were displayed within a green bounding box, indicating accurate detection and recognition. The stable FPS suggests that the system is optimized for real-time performance in various lighting and background conditions. These results demonstrate the effectiveness of the system in identifying and annotating faces with high precision.

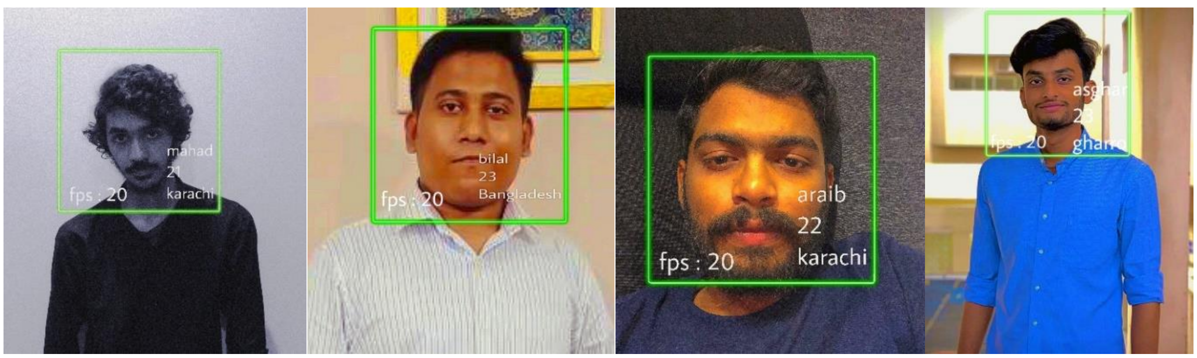

Figure 5: Real-Time Facial Recognition with Identity, Age, and Location Annotations at 20 FPS

Now, the results and statistics are shown here. The first figure presents the FPS distribution applied to four different subjects with three proposed facial recognition systems (LBPH, FaceNet, and Face_Recognition) across scenarios with varying numbers of faces in the frame: 0, 1, and 2 faces. Table 3 provides the FPS distributions across all applied algorithms, as shown in Figure 6.

1. **For 0 Faces**: The Face_Recognition system leads with 44% of the processing power, followed by FaceNet at 32%, and LBPH at 24%. This distribution shows that Face_Recognition achieves a higher FPS when there are no faces to process, suggesting its efficiency in low-activity scenarios.

Table 3: Processing power consumed by each applied algorithm in different face counts.

Number of Faces	LBPH (%)	FaceNet (%)	Face_Recognition (%)
0 Faces	24	32	44
1 Face	36	37	27
2 Faces	60	35	5

2. **For 1 Face**: The FPS distribution is more balanced, with LBPH capturing 36%, FaceNet at 37%, and Face_Recognition at 27%. This balance indicates a moderate load across systems when detecting a single face.

3. **For 2 Faces**: LBPH has the largest share at 60%, followed by FaceNet with 35%, and Face_Recognition at just 5%. This significant drop in FPS for Face_Recognition with multiple faces suggests a performance bottleneck in handling higher face counts compared to LBPH and FaceNet.

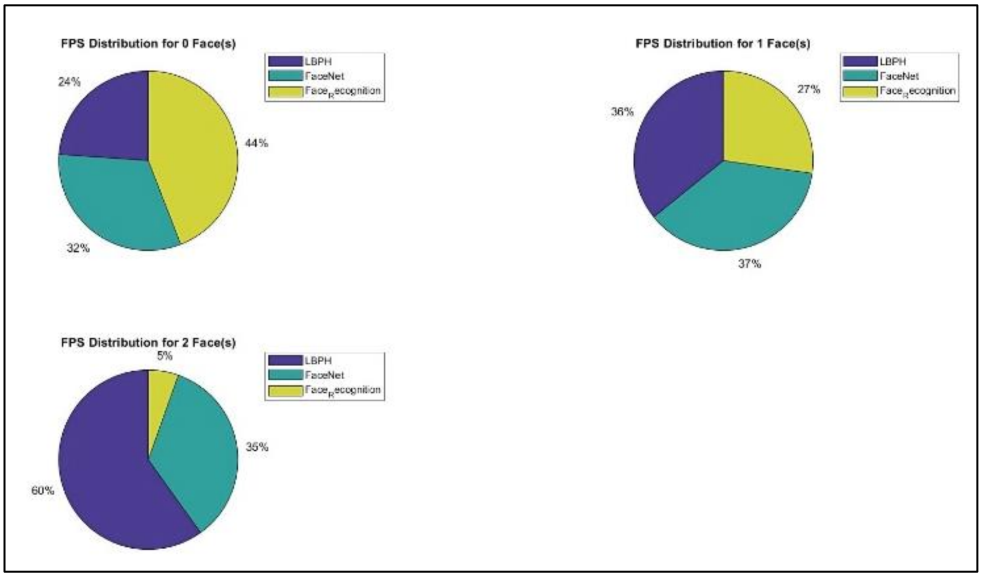

Figure 6: FPS Distribution Across Facial Recognition Systems with Varying Face Counts

B. Angle-based Facial Recognition

The second test was designed to measure the accuracy of all three systems when it comes to both facial detection and facial recognition. An exceedingly accurate facial detection and recognition system is needed for our tracking to work; that is why, for all three systems, the 25 minimum confidence thresholds for recognizing an individual were set to 80%. This test consisted of multiple variables, including the number of people in the frame and the angle at which each person was standing. Each test always consisted of one to three people in the frame. Those people were either directly facing the drone, were looking slightly away from the drone at a 45-degree angle, or were facing perpendicular to the drone at a 90-degree angle, as shown in Figure 7.

45 Degree **0 Degree** **90 Degree**

Figure 7: Face Orientation Variability: Comparison of Recognition Angles at 0°, 45°, and 90

1. **At 0°**: The accuracy is almost evenly split among the three systems, with LBPH and Face_Recognition each holding 34%, and FaceNet slightly lower at 32%. This balanced accuracy indicates that all three systems perform similarly when the face is fully frontal.

Table 4: Accuracy of algorithms across varying face angles.

Face Angle (Â°)	LBPH Accuracy (%)	FaceNet Accuracy (%)	Face_Recognition Accuracy (%)
0	34	32	34
45	27	38	35
90	14	42	45

2. **At 45°**: FaceNet shows a slight advantage with 38% accuracy, while Face_Recognition follows closely at 35%, and LBPH at 27%. This shift suggests that FaceNet has a slight edge when recognizing faces at a moderate angle.
3. **At 90°**: Face_Recognition achieves the highest accuracy at 45%, followed by FaceNet with 42%, and LBPH with a much lower 14%. This pattern indicates that Face_Recognition handles profiles or side views more effectively, whereas LBPH struggles with larger face angles.

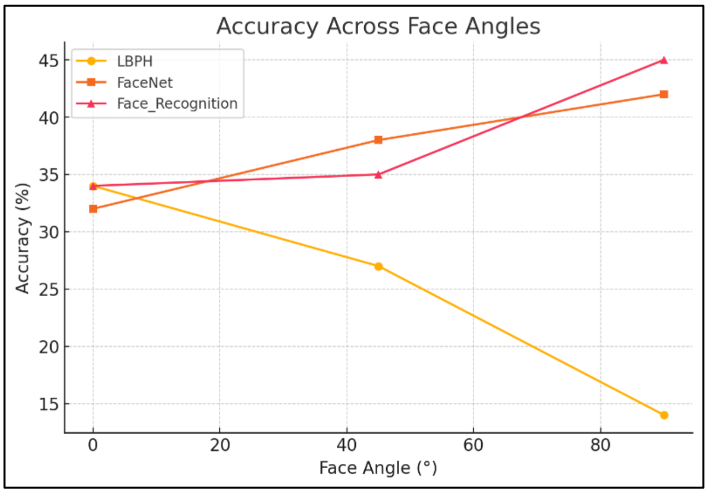

Figure 8: Performance metrics of LBPH, FaceNet, and Face_Recognition across varying face angles.

All the individuals in the frame were facing the same direction in each test, whether it was looking directly in the drone's direction or facing perpendicular to the drone. Experiments were not conducted with individuals facing more than 90 degrees away from the drone because, during preliminary testing, it was found to be incredibly hard to detect any faces from that angle, and we are testing facial detection and recognition, not head detection and recognition, as from that angle it becomes hard to see a person's face. The accuracy of each algorithm at varying angles has been shown in Table 4. Figure 8 displays the accuracy distribution of three facial recognition systems (LBPH, FaceNet, and Face_Recognition) at different face angles (0°, 45°, and 90°) with one face in the frame.

C. Distance-Based Facial Recognition

The final test was designed to measure the capabilities of all facial recognition systems when it came to searching and tracking a target person in real-time. This test was designed to see which facial recognition system functioned best when the entire system was used in a real-world setting. The drone was placed in a room with a preprogrammed surveillance path. Tests were conducted with two to five individuals in the room, one of whom Figure 7 was the target individual. The target was specified in the program beforehand, and the drone had the job of finding and tracking the target results. This test was designed to see if each facial recognition system could pick out the specified target from a group of people and if it could track the target once that individual was found. The drone's starting position was in the center of the room, and its 28 starting height from the ground was 2 meters. All the individuals started the test close to one another, standing in a group.

Table 5: Accuracy of algorithms across the varying distances from the face.

Distance (m)	LBPH Accuracy (%)	FaceNet Accuracy (%)	Face_Recognition Accuracy (%)

1	33	33	34
1.5	33	32	35
2	46	54	0
2.5	70	30	0

1. **At 1m**: Face_Recognition leads slightly with 34% accuracy, followed closely by LBPH and FaceNet, each at 33%. This relatively balanced performance shows that all three systems perform comparably well at close range as, depicted in Table 5.
2. **At 1.5m**: Face_Recognition again has the highest accuracy at 35%, with LBPH at 33% and FaceNet at 32%. This suggests that Face_Recognition maintains a slight advantage at this moderate distance.
3. **At 2m**: FaceNet captures the majority accuracy at 54%, while LBPH has 46%. Face_Recognition fails to detect the face accurately at this distance, resulting in 0% accuracy. This indicates that Face_Recognition effectiveness significantly declines as distance increases.
4. **At 2.5m**: LBPH achieves the highest accuracy at 70%, with FaceNet at 30%, while Face_Recognition remains ineffective at this distance with 0% accuracy. This pattern demonstrates LBPH's superior ability to recognize faces at longer distances, while Face_Recognition struggles significantly beyond 1.5m. Figure 9 illustrates the accuracy distribution of three facial recognition systems (LBPH, FaceNet, and Face_Recognition) at different distances (1m, 1.5m, 2m, and 2.5m) with one face in the frame.

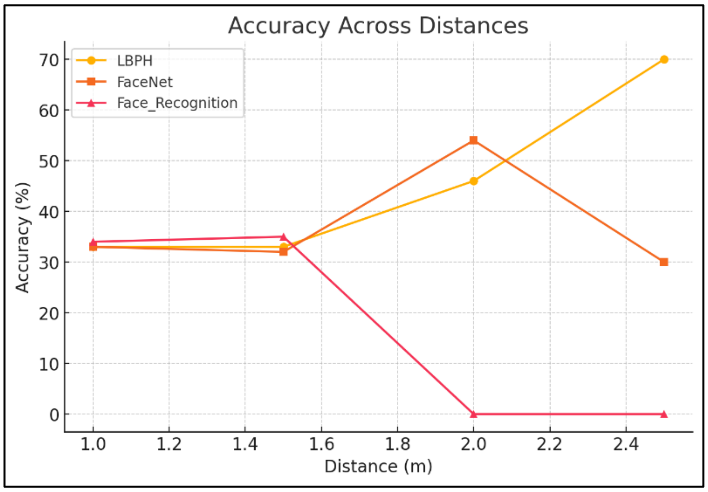

Figure 9: performance metrics of LBPH, FaceNet, and Face_Recognition across varying distances

The results demonstrate varying performance among the three facial recognition systems LBPH, FaceNet, and Face_Recognition across FPS, angle, and distance conditions. For FPS distribution, Face_Recognition achieves the highest frames per second when no faces are present. Still, its performance significantly drops as the number of faces increases, indicating limitations in handling multiple detections. In contrast, LBPH maintains a more consistent FPS, especially when there are multiple faces, showing its suitability for complex scenarios. When analyzing accuracy at different face angles, Face_Recognition performs well at extreme angles (90°), while FaceNet maintains steady accuracy up to 45°, suggesting that Face_Recognition is better at handling side profiles, whereas FaceNet offers more balanced accuracy across moderate angles. At various distances, Face_Recognition shows strong performance up to 1.5 meters but fails beyond that range, achieving 0% accuracy at 2 meters and beyond. In contrast, LBPH and FaceNet continue to deliver acceptable accuracy as distance increases, with LBPH emerging as the most effective at 2.5 meters. Finally, FaceNet provides stable performance across moderate circumstances, Face_Recognition outclasses in close-range and single-face scenarios, and LBPH is good at handling and recognizing many faces at larger distances. These findings suggest that LBPH may be better suited for surveillance in larger spaces, while Face Recognition could be effective for close-up, low-activity monitoring.

VI. CONCLUSION

The study aims to analyze the performance of parametric variations of facial recognition systems, i.e., angle and distance, through UAV imagery in urban environments for safety concerns. The whole facial recognition system has been tested in a controlled environment, i.e., a lab with different subjects with varying angles as well as distances. The proposed system consists of an image processing technique convolution neural network along with three facial recognition systems, FaceNet, Face Recognition, and Local Binary Pattern Histogram, for the successful recognition of the target face in public. The testing was done in three phases: Frame per second distribution, varying angle test, and varying distance test at a state-of-the-art laboratory. The test was conducted on four subjects with known names, ages, and locations at 20 frames per second. The result analysis shows that the accuracy of detection by Face Recognition leads to multiple face detection, while FaceNet leads in varying angles LBPH at larger distance detection. The comparative analysis of this study shows that the minimum confidence threshold achieved is 80%. The proposed work can be enhanced by adding more target images into datasets, implementing the proposed algorithm in an autonomous drone, and combining different algorithms to find more accuracy.

CONFLICT OF INTEREST

There is no conflict of interest between all the authors.

DATA AVAILABILITY STATEMENT

Upon request data will be shared with concerned authorities with mutual understanding.

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