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Motion-Watch Using Python and OpenCV

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ABSTRACT: Motion-Watch is an AI-driven smart surveillance system developed to offer intelligent, real-time monitoring with minimal human intervention. The system is designed to capture, analyze, and respond to activity within a given environment using live video feed from a connected camera. At its core, it employs advanced motion detection algorithms, filtering out noise and static frames to focus solely on relevant movements. One of the system's standout capabilities lies in its face detection and recognition engine, which uses either LBPH or deep learning models to distinguish between known and unknown individuals. Upon identifying an unfamiliar face, the system instantly triggers alerts through an integrated Telegram bot, ensuring that the user is promptly informed of any potential intrusions-regardless of location.

Motion-Watch also supports dynamic direction tracking, enabling users to monitor the in-and-out flow of people through specified zones, thus enhancing situational awareness. Each event is logged with a timestamped image or video, which is automatically stored for future review and evidentiary use. Designed with scalability and adaptability in mind, Motion-Watch is equally effective in domestic, office, or commercial environments. It offers cross-platform compatibility and leverages Python's rich ecosystem of libraries for robust performance. The application is lightweight, deployable on moderate hardware, and capable of running continuously without performance degradation. In essence, Motion-Watch merges the power of artificial intelligence, real-time data processing, and user-friendly interaction to deliver a reliable and intelligent security solution tailored for modern-day needs. It redefines surveillance not just as a passive system, but as an active, intelligent assistant.

KEYWORDS: Motion detection, Face recognition, Surveillance system, Real-time monitoring, OpenCV, Python, LBPH algorithm, Noise reduction, In-Out tracking, Snapshot storage, Telegram bot, Security automation, Event logging, Camera feed, Object detection, Smart alert system, Intrusion detection, Visual analytics, Frame processing, User interface.

I. INTRODUCTION

The growing demand for real-time monitoring in homes, businesses, educational institutions, and commercial areas has transformed surveillance systems into a core part of modern security. Traditional CCTV cameras need manual monitoring and are limited to video recording; they are ineffective when rapid action is necessary. Emergent strong solutions to these issues are computer vision-based smart monitoring. obstacles. Created using OpenCV and Python, Motion Watch is an automatic vision-based monitoring system with intelligent identification detection and alert features. The system scans live video feeds senses motion in the surroundings and determines whether the. The person in the frame could be known or unknown. The system immediately notifies the owner after photographing an unlawful or unidentified person. Specialized Telegram bot helping to raise awareness of security and expedite decision-making. Modules like monitor and identity improve the system's dependability and efficiency. noise reduction and rectangle automatic recording in-out tracking. By deleting unwanted interferences from the frame, the noise module lessens false positives or identities. Real-time facial identification is used by the module to sort people. The in-out module aids the system in recognizing entrance and departure patterns by means of additional movement. Motion Combining these modules, Motion Watch aspires to offer smart observations and immediate reactions, therefore closing the gap between conventional monitoring and contemporary smart security systems. Python and OpenCV are popular for image processing because of their great performance, adaptability, and thorough feature set. The underlying technologies are

OpenCV. Automation, real-time processing, and create a cost-effective, user-friendly, very flexible system fit for several security uses.

II. LITERATURE SURVEY

Computer vision-based surveillance research has mostly concentrated on increasing automated alerting, identity recognition, and motion detection to improve security systems. Subsequent studies added Gaussian blur and morphological filtering as preprocessing methods to stabilize movement detection and minimize noise. From simple Haar cascades and LBPH approaches to more precise deep-learning techniques, face detection and recognition have grown such as to enhance the ability to identify both known and unknown persons. Studies also stress how combining movement detection with identity verification increases real-time surveillance real-time reliability. [1]. One of the first and most effective methods for real-time face detection, the Viola-Jones Face Detection Framework (2001), is thus very pertinent to surveillance efforts like Motion Watch. It presented Haar-like characteristics that capture human facial patterns rapidly. Using the AdaBoost algorithm, which chooses the most effective features and lessens unwanted computations, was a major new idea. Furthermore, the framework employs a cascade classifier structure that swiftly removes non-face areas and targets processing power only on probable face regions. Like the real-time monitoring need of your project, this let face detection operate flawlessly even on modest powered devices. [2]. The system may distinguish between moving objects and the background even under changing lighting or environmental situations by treating every pixel as a combination of Gaussian distributions. Because of its dynamic modeling, GMM is rather useful for real-time monitoring; noise, shadows, and tiny motions might all cause false positives. GMM helps to notice genuine movement in initiatives like Motion Watch by continually learning what belongs to the background and what fits as a new object coming into the scenario. In [3]. One of the most widely used techniques for finding people in images and movies is HOG + SVM person detection suggested by Dalal and Triggs in 2005. HOG, or Histogram of Oriented Gradients, picks up the edges and gradients that define a person's shape, and it doesn't get thrown off by changes in lighting. Pair that with a Support Vector Machine—SVM for short—and you've got a combo that sorts out people from the background with impressive accuracy. This method shines in monitoring systems because it holds up even when part of a person is hidden, when they're in different poses, or when the camera quality isn't perfect. In [4] With the launch of Face-Net in 2015, which moved the emphasis from conventional feature extraction to learning very precise facial embeddings, deep learning-based face recognition experienced a great success. In [5], Modern security systems based on IoT combine cameras, cloud services, and message APIs to allow real-time monitoring, as shown by recent studies spanning 2020 to 2024. When you bring computer vision and IoT together, you get systems that can spot movement, recognize faces, and send warnings right to your phone over Wi-Fi or mobile data. Studies show that hooking up IoT cuts down response times and gets alerts to users instantly, usually through devices like smartphones. A lot of setups, including the Motion Watch project, use Python and OpenCV, running on microcontrollers or single-board computers with lightweight models.

III. PROPOSED METHODOLOGY

The heart of this intelligent surveillance system lies in its ability to mimic human-level awareness through seamless real-time processing. The journey begins as the IP camera streams continuous video footage, which is immediately refined using Gaussian Blur and Median Filtering techniques that intelligently smooth out grainy frames and eliminate background noise caused by dim lighting or sensor disturbances. This foundational step ensures visual clarity, preventing false triggers and preparing the data for deeper analysis. Next, the system leverages the MOG2 background subtraction algorithm, which learns the natural scene over time and identifies meaningful movement by filtering out irrelevant shifts like shadows or rustling leaves. Once motion is confirmed, the pipeline automatically initiates face detection, using Haar Cascades to precisely locate human faces in the frame with impressive accuracy and speed. Once a face is spotted, the system enters the identity recognition phase. Here, it can flexibly switch between LBPH, ideal for quick and lightweight facial matching even in low-light settings, or CNN-based deep learning models when high-precision is needed. If the face matches an authorized profile, the system silently continues surveillance. However, if the individual is unrecognized, it captures a timestamped snapshot, logs the event, and activates the Telegram Bot API to send an immediate alert with the photo attached directly to the user's device for instant situational awareness. Simultaneously, the In-Out Tracking module interprets the direction of the subject's movement using centroid-based logic and optionally SORT tracking, providing rich contextual data like entry or exit timestamps. This enhances the system's role not just as a monitoring tool, but as an intelligent observer capable of logging human behavior patterns. By integrating all modules in an event-driven architecture, the system conserves resources by only reacting when activity warrants it. This ensures optimal performance while delivering a highly responsive, smart security framework tailored for modern environments.

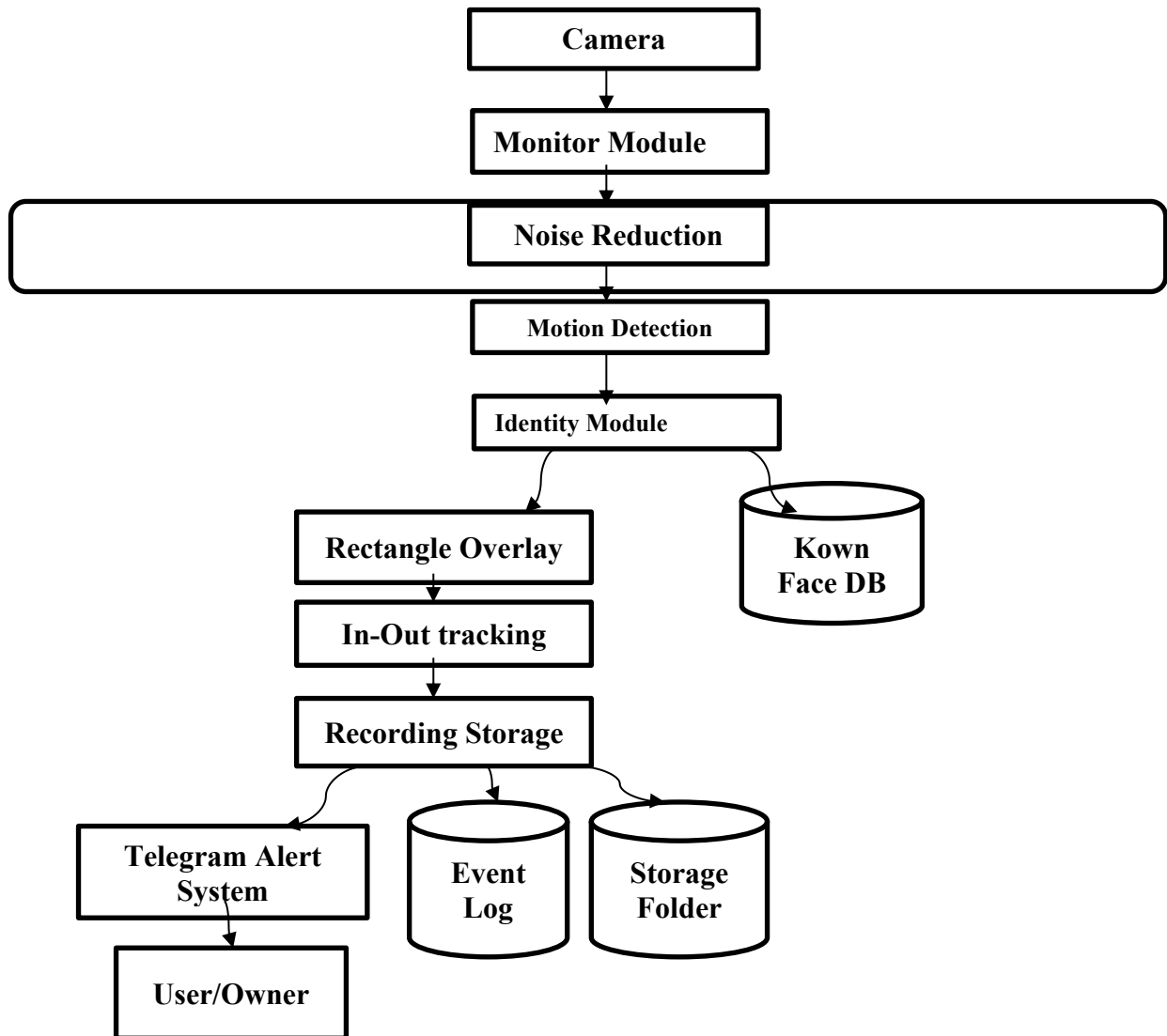


Fig. 1 Data Flow Diagram

The intelligent surveillance framework starts with the Camera capturing a continuous real-time feed, acting as the system's visual gateway. This feed is directed into the Monitor Module, which processes each frame in real time like the human eye observing and evaluating the surroundings. Before deeper analysis, the input undergoes Noise Reduction, where the system intelligently cleans up visual distortions such as graininess or low-light interference. This ensures that only relevant and clear visuals move forward for further detection, minimizing false alarms. The cleansed video stream is passed into the Motion Detection module. Here, the system mimics the brain's ability to detect movement using advanced algorithms like MOG2, accurately identifying only true motion amidst subtle environmental fluctuations. Upon detecting movement, the system activates its Identity Recognition engine. Using techniques like Haar Cascades and LBPH or deep-learning models, it identifies whether the person in view is Known (pre-registered in the Face Database) or Unknown. This layer enables intelligent differentiation rather than treating all motion as suspicious. Once identification is confirmed, the system highlights individuals using Rectangle Overlay, drawing precise bounding boxes around the detected faces or figures. This adds clarity for both visualization and later review. The In-Out Tracking logic then comes into play, tracking the directional flow of movement whether someone is entering or exiting a zone. This mimics human spatial awareness and adds contextual meaning to movement patterns. Simultaneously, the system activates the Recording Storage module. It automatically captures snapshots and video clips of critical events, embedding timestamps, and saving them securely in Event Logs and Storage

Folders for audit trails or evidence gathering. If the individual is labeled as “Unknown,” the system immediately triggers the Telegram Alert System, sending a real-time notification (including the captured image) to the User or Owner. This ensures proactive threat awareness even when the user is remote.

The algorithms used in this project include Gaussian Blur, Median Filtering for noise reduction to ensure clean and stable video frames, MOG2 Background Subtraction to identify motion through the difference between frames, and LBPH for real-time speed or CNN for high-accuracy deep learning for face recognition. All these combined enable efficient tracking and identification of motion.

1. Gauss Blur: Smoothing of frames can be done by the Gaussian Blur that will remove random pixel fluctuations, which normally occur in low lighting conditions or due to interference from the camera itself. It reduces the effect of noise; hence, the frames will become more consistent, making them visually stable, thereby enhancing the accuracy of successive steps of processing to a great extent. It also prevents the system from triggering false motion alerts because of flickering lights, dust, or some minor pixel distortions. The clarity of the subject in the frame increases, and both motion and face detection algorithms are effective and run more efficiently. Without this step or stage, the system would be prone to frequent false alarms and unstable detection behavior.

2. Frame Differencing + Background Subtraction: It examines the input video feed for motion, where the system compares each video frame against a static or dynamically generated background frame. Using the MOG2 methodology, the proposed solution segregates dynamic objects through the subtraction of the background and highlighting of dynamic regions of interest, such as human movement. When enough motion above a threshold value is detected, the processing pipeline proceeds with the recognition stage; otherwise, if not enough motion is detected, the surveillance system sits in an idle mode to save computational resources and storage.

3 Local Binary Patterns Histogram[LBPH]: During the identification process of the detected individual, the system extracts facial features of the detected person and correlates with the stored identity information to establish whether the person is known or not. The LBPH algorithm guarantees faster identification even under low light or real-world conditions, while CNN offers higher accuracy because of deep learning. The choice between algorithms depends on performance requirements. If the identified individual is known, it continues the normal surveillance without disturbing the user. If the detected individual is not found in the database, it enters alert mode as one could be trying to access without authorization.

4. Object Bounding Box Algorithm: Once the individual face or human presence has been confirmed, the Rectangle Overlay Module outlines a bounding box on detection around the individual using contour detection or Haar Cascade regions of interest. This live visual overlay assists the user in identifying the active person in the feed of the surveillance camera and confirms that the detection and tracking modules are responding correctly. The overlay adjusts dynamically when the person moves inside the frame, enhancing usability in real-time monitoring accuracy.

5 Centroid Tracking/SORT Tracking: For the In-Out Tracking Module, a decision is made on whether the detected person is entering or exiting the monitored area to understand the behavioral pattern of the subject. Centroid Tracking or SORT tracking is done to trace the movement path of the subject in sequential frames. This will help in identifying suspicious/abnormal motion patterns such as reverse entry or loitering, while timestamps are automatically logged for future evidence. Offering directional awareness improves home and workplace security.

Testing: Once we had managed to integrate all the modules together into a single workflow, we began testing the system to check how it would behave. We tried to check if it was capable of detecting motion, identifying people, tracking movement, drawing bounding boxes around people detected, storing videos, as well as alerting people.

1. Unit testing. We began with something simple. Each and every component had its own testing done. Detection, removal of noise, recognition, verification, tracking entry and exit, picture storage, and Telegram alerts - all these functions had to demonstrate they could process random data and generate correct outputs independently. They all worked as they should, so we were ready to integrate everything.

2. Integration Test: After witnessing each module functioning on its own, we connected these modules. The tracking, storage, alerting, recognition, and live stream cameras all needed to get along within a single large process. They needed to communicate with each other. Images flowed effortlessly, and information exchanged as it should, without any loss in speed or functionality. None of it crashed. It all worked together as a unit.

3.Functional testing: At this stage, we were curious about the functionality offered by the system. So, we tried testing it on all the large functionalities, including motion detection, stranger/friend recognition, familiar faces highlighted, people tracking, saved snapshots, and alert sent. It ached every single task on our list. The system reached every target, and customers received exactly what we were aiming to provide.

4. Performance Test: We pushed it as hard as it could be pushed to check if it truly satisfied our needs as set forth within our specifications. Could it detect motion, identify a friend from a stranger, identify faces it recognized previously, track people, take a photo, and alert as soon as it detected something new? It passed with flying colors. It does exactly what it's supposed to.

5. Security Testing: We wanted to ensure that the system effectively locked down confidential data and maintained user privacy. Only authorized people had access to Telegram messages or viewed images. We ensured that the recognition logic ensured that no one could sneak into the system without authentication. Even if someone attempted to intervene with data, the system maintained data security and privacy.

6. User Acceptance Testing(UAT): We brought in real people and let them jump into operation without any guidance and see what it would be like. They caught on quick. The alert notifications, and particularly those with pictures, made it easy to react if something

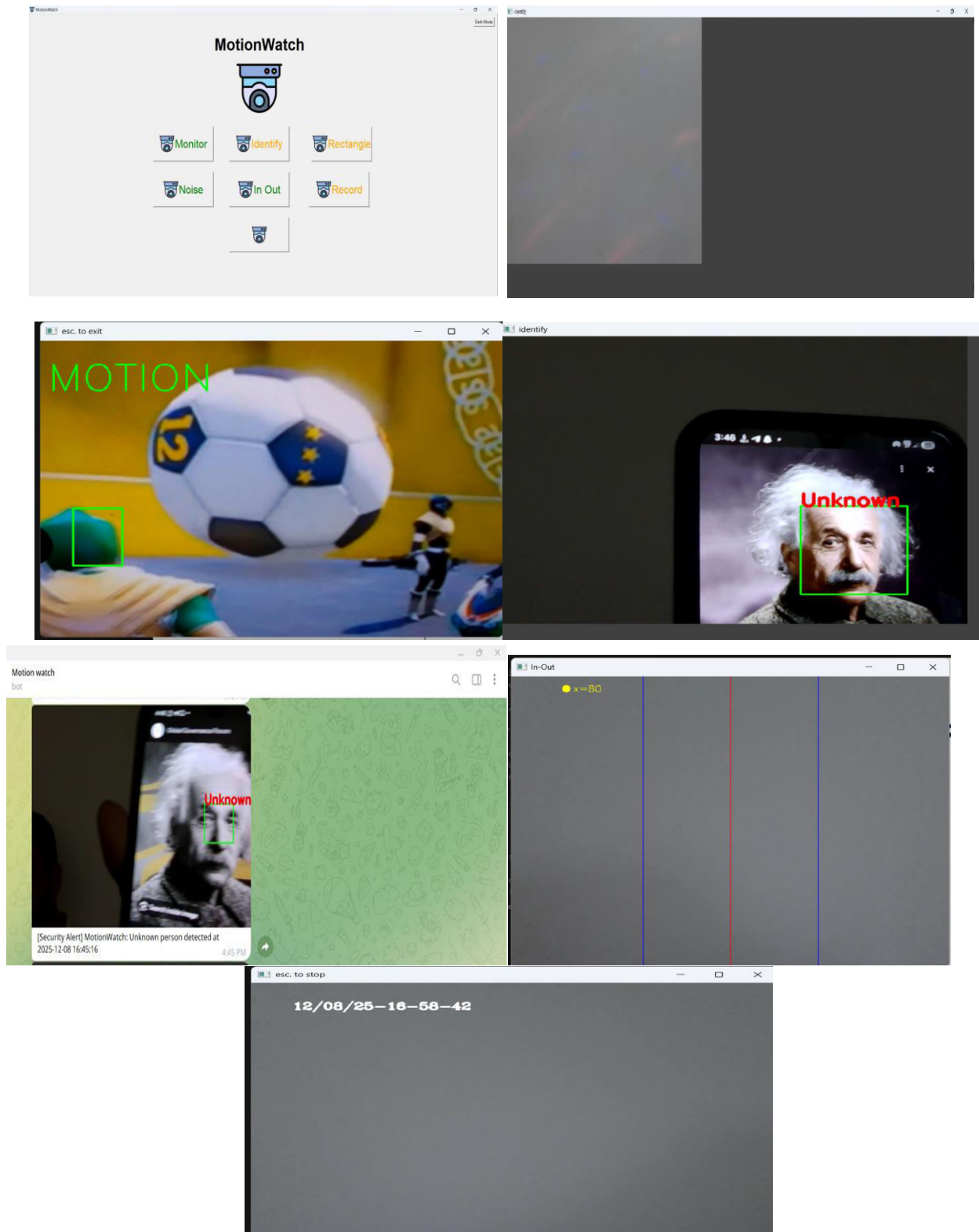
bad was going on. Everyone liked how easy it was and how reliable it all seemed. Bottom line: it's more than just a secure and intelligent system – it's easy to operate at home and at work.

Test Cases:

Test Case ID	Description	Input	Expected Output	Result
TC-01	Validate real-time camera stream initialization	User activates the monitoring module	System seamlessly launches a live video stream without latency or disruption	Pass
TC-02	Assess image clarity enhancement in noisy visual conditions	Frame captured under low-light or noisy conditions	Frame is auto-corrected to suppress noise, delivering a visibly cleaner image	Pass
TC-03	Ensure responsiveness of motion detection system	Human or object enters camera view	Movement is promptly detected and control shifts to face detection & tracking	Pass
TC-04	Confirm facial detection mechanism in active video feed	Human face is visible within camera frame	Haar-Cascade algorithm identifies and highlights the facial region precisely	Pass
TC-05	Verify recognition and labeling of known individuals	Previously registered face enters frame	Face is labeled as Known, and alert mechanism is bypassed	Pass
TC-06	Check alert response on unknown individual detection	Unknown/unregistered face appears	Face is flagged as Unknown, alert is triggered, and snapshot is processed	Pass
TC-07	Validate visual bounding box overlay during detection	Face/body appears in real-time	A bounding rectangle is dynamically placed with accuracy on detected regions	Pass
TC-08	Evaluate directional tracking accuracy (In-Out module)	Person crosses detection zone	System accurately determines and displays entry (IN) or exit (OUT) direction	Pass
TC-09	Check if snapshots are saved upon unauthorized detection	Unknown entity detected during monitoring	Image is automatically captured and saved with timestamp metadata	Pass
TC-10	Validate instant notification system via Telegram bot	Snapshot of unknown person captured	Alert with image is delivered instantly to authorized user via Telegram	Pass
TC-11	Confirm alert acknowledgment and resume logic	User responds to alert on Telegram	System logs the acknowledgment and monitoring continues seamlessly	Pass
TC-12	Ensure stable behavior during idle surveillance	No activity is detected in frame	Monitoring continues passively with no false alerts or unnecessary interruptions	Pass
TC-13	Verify clean and safe termination of application	User issues quit command	System-halts-gracefully, closes-streams, and exits without error	Pass

IV. EXPERIMENTAL RESULTS

Motion-Watch represents a next-generation intelligent surveillance ecosystem, seamlessly integrating multiple modules to elevate traditional security systems. At its core lies a visually intuitive interface, allowing users to effortlessly navigate functions such as real-time monitoring, face identification, motion tracking, and evidence recording. Once activated, the system initiates continuous video capture, filtering out visual noise to ensure clarity, even in low-light or unstable environments. Through dynamic motion detection, powered by robust algorithms like Gaussian Mixture Models, it discerns real movement while minimizing false alarms.



It can classify people smartly into "known" or "unknown", referencing a pre-trained database and visually labeling the faces with bounding boxes. Most importantly, once an unrecognized face is detected, the system triggers an alert via a secure Telegram channel immediately, attaching timestamped evidence for out-of-place notifications. The motion recognition would go down to directional

movement analysis through digital boundary tracking, thus enabling correct IN/OUT logging for entry zones. Events will be archived chronologically and are supported with detailed logs and snapshots for forensic traceability. Its real-time decision-making and flexibility enable it to ensure that alert and record capabilities are only activated when it identifies a potential threat. As a result, the system is built on such a light architecture that it can detect movement in homes, workplaces, and small businesses without the need for expensive CCTV cameras. Utilizing automation, communication, and computer vision, Motion-Watch surpasses all conventional methods and provides users with a flexible and powerful security system.

V. CONCLUSION

Even if its implementation is possible, Motion-Watch nonetheless represents a significant step in the direction of smart surveillance, which will ultimately be implemented from both a personal and commercial standpoint. You will have a surveillance system that is comprehensive, practical, and quick by combining old-school surveillance methods with intelligent AI functions like recognition skills, noise reduction, motion detection, and detection direction. Its inherent modular functionality will allow you to modify it to fit any circumstance. Your own opinion will determine which features you want and what you want from it, regardless of whether it's a house neighborhood with little room or an office floor with a lot of foot traffic. Anyone with no prior technical knowledge will find it simple to use due to its real-time processing, low-latency video capabilities, and user-friendly interface. Due to additional capabilities pertaining to entry and exit monitoring and alarm signals through Telegram, you will be able to approach any given topic in a more timely and less complicated manner. With regards to who might be intended to be inside entrance and exit, the surveillance system will be able to avoid false alarms and will instead notify you of what might be occurring. The thoughtful and artistic design will increase functionality and usefulness by paying close attention to icons and controls. Using and incorporating Python, OpenCV, Haar Cascade, and GUI SDKs and libraries from a developer's standpoint demonstrates professionalism and proficiency in today's modern tools and programming techniques. Because the unit testing, verification and testing, and system testing phases will all be successfully verified, it will serve as a unique demonstration of stability and functionality. Furthermore, there will be moments and chances to improve its cloud synchronization and multi-location features in later stages. From a broader viewpoint, anything as commonplace and straightforward as a surveillance camera is insignificant compared to what it represents. It establishes a massive and beneficial foundation for bridging numerous divides in technology and safety.

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