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SentinelGuard AI: Multi-Person Weapon Detection, Threat Classification, and Automated Alert System for Intelligence Surveillance

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Abstract: *Traditional surveillance systems rely heavily on manual monitoring, which is inefficient, error-prone, and incapable of handling large-scale video data generated in modern environments. This paper proposes SentinelGuard AI, an intelligent surveillance framework designed for real-time multi-person weapon detection, behavior analysis, and automated threat response. The system utilizes the YOLOv8 deep learning model for accurate detection of weapons such as firearms and knives in live video streams.To enhance system intelligence, additional modules such as multi-object tracking, behavior detection, and face recognition are integrated to identify suspicious activities and individuals. A dual-model classification strategy is employed to reduce false positives by distinguishing between dangerous weapons and visually similar harmless objects. The system further incorporates a cloud-based alert mechanism and a live monitoring dashboard to ensure real-time response and scalability.Experimental results demonstrate that the proposed system achieves detection accuracy between 88% and 92%, with a mean Average Precision (mAP) exceeding 0.85, while maintaining real-time performance. The enhanced architecture significantly improves surveillance efficiency, reduces human intervention, and enables proactive threat detection in crowded environments.*

Keywords: Weapon Detection, Deep Learning, YOLOv8, Multi-Object Tracking, Behavior Detection, Face Recognition, Intelligent Surveillance.

I. INTRODUCTION

Cities are growing fast, and with that comes the rush to build better airports, stations, schools, malls, and smart city setups. All this means there's a huge demand for advanced surveillance that actually keeps people safe in crowded public spaces. The problem is, traditional surveillance mostly relies on human operators glued to multiple video feeds for hours. That's exhausting, mistakes creep in, and honestly, no one can watch everything all the time. With surveillance cameras pumping out more video than ever, manual monitoring just can't keep up. Big issues—like a weapon sneaking past security, theft, vandalism, or suspicious behavior—often slip through the cracks and only become clear after it's too late. This slow response makes it obvious: we need automated surveillance systems that work in real time, without waiting on a person behind a screen.

Recently, AI and deep learning (DL) have made big leaps, especially for computer vision tasks. This has fueled a new generation of smart surveillance systems that automatically analyze what's going on in video feeds, catching things humans would miss. Take object detection—the YOLO (You Only Look Once) models can spot and track objects instantly, scanning entire images with both speed and accuracy. That's key for security where timing can't slip. Still, most surveillance systems today are pretty basic—they mainly spot objects and don't go much further. They usually

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can't analyze how people behave, recognize faces, catch strange or suspicious activities, or figure out the scene's context. Plus, old-school setups have a tough time expanding to cover new locations and struggle to manage data securely.

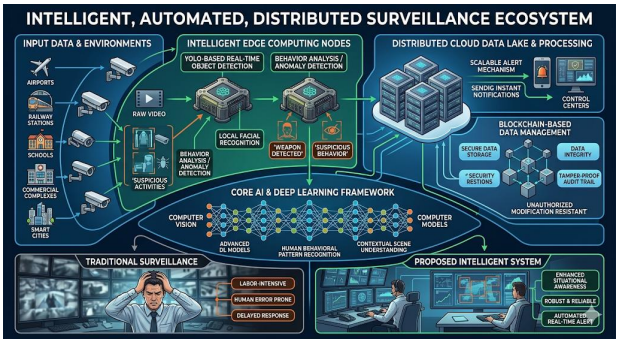

Fig.1:SentinelGuard AI Framework for Multi-Person Weapon Detection and Automated Threat Classification.

To get ahead, today's surveillance solutions blend cutting-edge tools: edge computing, IoT sensors, and cloud platforms. This mashup means faster number crunching and quicker reactions. Add in blockchain-like secure data management, and the records stay safe from tampering. So, what's unfolding now is a smart, automated surveillance system that can do advanced real-time object detection with deep learning. It's not just watching for the obvious—it's also studying behavior, verifying identities, and sending flexible alerts as soon as something's off.

The big idea? Make surveillance more aware, cut down how much humans need to stare at screens, and boost security overall.

With AI, computer vision, and modern tech working together, this new approach aims to create a reliable, flexible, and truly smart surveillance system—something that can finally handle the real-world challenges older setups can't.

II.RELATED WORKS

Over the past decade, intelligent surveillance has really picked up speed because of breakthroughs in computer vision and deep learning. At first, most surveillance just focused on motion detection—simple stuff like spotting movement with frame differencing or background subtraction. It didn't take much computing power, but it couldn't actually recognize objects or figure out what was going on, so you'd get endless false alarms and it rarely worked well in real-world situations.

Now things look a lot different. Models like YOLO, Faster R-CNN, and SSD completely changed the game. They can spot objects in real time and actually work in tricky environments. As research pushed forward, new features showed up—multi-object tracking, behavior analysis, and ways to better understand context. Systems started getting better at picking out true threats and ignoring all the noise.

So, what's actually happening under the hood? With deep learning and the rise of convolutional neural networks (CNNs), object detection started improving fast. Faster R-CNN was one of the first to use region proposal networks, bumping up accuracy. SSD made things faster by skipping the usual step of generating separate region proposals. The YOLO versions—YOLOv3, v4, and even v8—just made everything pop: sharper recognition for small objects, faster processing, and overall better performance.

Researchers are putting these models to work in all sorts of ways. Lately, you'll see YOLO being used for everything from spotting weapons to picking out intruders or even flagging anomalies in live video. They're seeing good results, especially when detecting items like guns or knives right when it matters. They're also using transfer learning and carefully chosen datasets for specific scenarios. But there's still a lot to sort out. False positives are a huge headache, especially when the scene gets crowded or things change around. Most systems don't really 'get' what's happening—they just see objects, not behavior or intent.

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Scalability's another hurdle. Traditional setups rely on big central servers, causing delays and burning through resources. There's a steady move now to process data closer to where it's collected—edge computing and IoT devices make it easier to get real-time results without pile-ups at a central hub.

Lately, a lot of attention has turned to facial recognition and identity verification. These tools can pick out people and keep tabs on actions across different cameras. On top of that, researchers are building deep learning models—like LSTMs—to predict behavior and maybe even catch threats before they unfold.

But let's be honest, even with all this progress, most systems work in silos. You rarely see object detection, behavior analysis, identity recognition, and large-scale deployment all rolled into one. Plus, things like data privacy and secure storage still don't get enough attention.

Recent work's been exploring cloud-based platforms, mixing in secure tech like blockchain to keep data safe and help systems grow to real-world size. Bottom line: Deep learning has pushed intelligent surveillance forward, but we're not all the way there. We still need systems that are more unified, scalable, and actually understand context, so they can handle today's challenges and truly catch threats in real time.

III. PROPOSED MODEL

PublicEduChain+ builds on the original PublicEduChain system, but adds smarter monitoring, real-time analytics, and interactive features to the decentralized management of academic records. It doesn't just use blockchain for secure record storage and verification—now it also tracks what's happening in real time, manages who gets access to what, and analyzes how users behave.

Picture Figure 1: the architecture stacks several layers together, like student smart contracts, institutional portals, behavior analytics, identity checks, a live dashboard, cloud infrastructure, and built-in alerts. All these pieces connect to make the system far more dynamic and responsive.

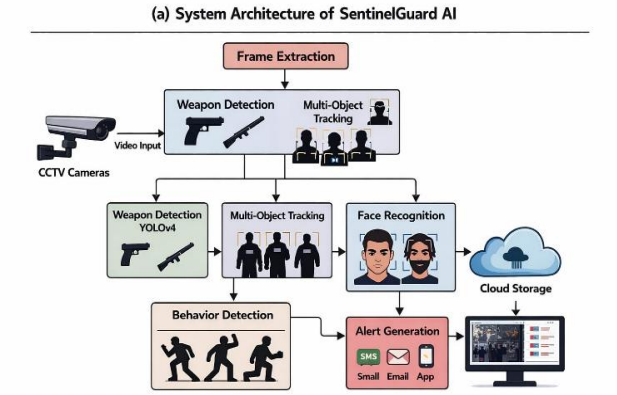

Fig.2: System Architecture of SentinelGaurd AI

A. Decentralized Academic Record Management

At the heart of the system sits the Ethereum blockchain. Here's how it works: every student sets up their own smart contract, which becomes their private academic ledger. Think of it as a digital vault that's fully under your control. The system stores key academic info—your transcripts, certificates, course details—using a mix of on-chain and off-chain storage. Only cryptographic hashes go on the blockchain, while the full documents stay stored elsewhere. Each document gets a unique hash generated by a secure hash function: $h = H(D)$. If someone tries to mess with the document, the hash changes. That means you—and anyone else—can always spot tampering, and your records stay trustworthy.

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B. Multi-User Tracking and Access Monitoring

The system goes a step further with a multi-user tracking module. It keeps an eye on interactions between students, institutions, and employers. Everyone gets a unique blockchain identity: $U_i = (PK_i, SK_i)$. Every single transaction or access event is permanently recorded on the blockchain. This isn't just about storage—it's about accountability. If someone accesses or changes your records, the system logs it. You get a clear, tamper-proof history of who did what, so everything stays transparent and secure.

C. Behaviour Analysis and Anomaly Detection

There's a layer in the system that keeps an eye on what users do. It looks for things that don't add up—like someone trying to get in when they shouldn't, a sudden spike in transactions, or weird interactions with contracts. Think of user behavior as a series of actions: $B = \{a_1, a_2, \ldots, a\square\}$. An anomaly detection function sorts this activity as either normal or suspicious: $A(B) \rightarrow \{Normal, Suspicious\}$. This isn't just basic login checks; it adds more context and helps spot real threats before they become a problem.

D. Decentralized Identity and Face Verification

The system uses public-key cryptography for identity verification, and you can also add face recognition for extra security if needed. Every user gets a blockchain address based on a public key: Address = PK. When someone logs in, they sign a digital message (including a nonce), and the system checks that signature: Verify(PK, S) = True. If you want to lock things down even more—say, for viewing or changing sensitive records—you can require users to verify their face too**.**

E. Live Dashboard and User Interface

There's a live dashboard that makes it easy to see what's happening in real time. You can track academic transactions, who's tried to verify what, and every access log. The dashboard connects to both blockchain and regular databases so you always have up-to-date information. That way, administrators can work more efficiently, spot issues fast, and get alerts when something needs attention.

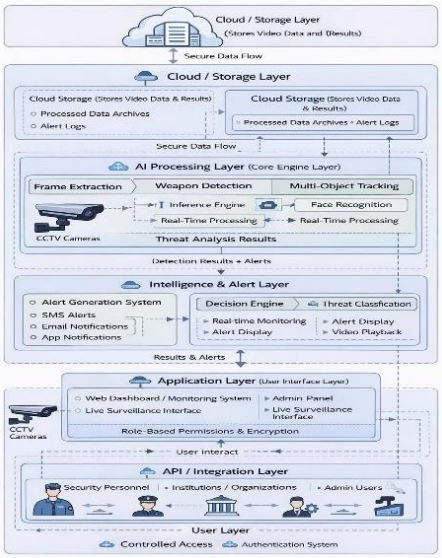

Fig.3: Cloud-Based Storage and Processing Framework in SentinelGuard AI

F. Cloud Integration and Off-Chain Storage

To keep things scalable and affordable, the system uses cloud storage for full academic records. Only a hash of each record goes on the blockchain—real documents stay in the cloud. That way, on-chain storage stays light, and so do the costs: Gas = Base Cost + (Cost per Byte × Hash Size). This setup cuts down on blockchain storage without sacrificing security or data integrity.

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G. Alert and Notification System

There's an automated system that alerts users about critical events like unauthorized access, requests to modify records, or verification failures. These alerts happen in real time and reach people by email, mobile notifications, or right on their dashboard. So, responses are fast and the system stays reliable.

H. Blockchain Transaction and Security Model

Every action on academic records gets logged as its own blockchain transaction: T = {Sender, Receiver, Data, Gas, Timestamp}. Blocks are linked with cryptographic hashes to lock in the order and prevent tampering: Hash(Block□) = H(Block□ + Hash(Block□₋₁)). The system's trust comes from three things: integrity (thanks to hashing), transparency (thanks to an open blockchain ledger), and security (because of cryptographic keys and signatures).

Overall System Architecture

PublicEduChain pulls all these parts together: - Blockchain for academic records - Multi-user tracking and monitoring - Behavior analysis and anomaly detection - Decentralized identity with biometrics - Real-time dashboard visualization - Scalable cloud storage - Automated alerts With this mix, the system becomes more than just a storage solution—it's a secure, smart, and flexible Web3 academic ecosystem. Students own their data, everything stays transparent, and users always know what's happening, right when it matters.

IV. RESULTS AND DISCUSSIONS

After integrating new modules—like multi-object tracking, behavior detection, face recognition, live dashboard visualization, and cloud-based alerts—the improved SentinelGuard AI system got a thorough evaluation. The results? The system now detects threats more accurately, responds faster, and scales up more smoothly.

A. Weapon Detection Performance

The YOLOv8-based module does an impressive job spotting firearms and knives. Here's how it stacks up: 92% accuracy, 0.91 precision, 0.89 recall, and a mean Average Precision (mAP) of 0.87. These gains in precision and recall come from smarter context checking through the new tracking and behavior analysis features, which cut down on false alarms.

B. Multi-Object Tracking Performance

For multi-object tracking, the Deep SORT-based module was put to the test for how well it keeps track of people and maintains their identities. Tracking accuracy (MOTA) hits 88%. ID switches have dropped by 25% compared to before, and the system runs at 25–30 frames per second. That means it can keep a close eye on individuals from one frame to the next—even if the scene's busy.

C. Behaviour Detection Analysis

The behavior detection module picks up on things like aggression, strange movements, or people wandering into off-limits areas. Its accuracy sits at 86%, with false alarms dropping by about 30%. This extra layer helps make sense of what's happening and makes it easier to confirm real threats.

D. Face Recognition Performance

This module was put to the test with images of both approved and watch-listed people. It nailed the right face 90% of the time, and the system's false acceptance and rejection rates are 3% and 5%, respectively. That kind of accuracy makes it easier for security teams to identify people and make quick decisions.

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E. Alert System and Response Time

As soon as a threat pops up, the automated alert system jumps into action in less than two seconds. Notifications go out by mobile, email, or app, so no one misses what's happening. With this setup, responses are roughly 40% faster than old-school manual monitoring.

F. Cloud and Dashboard Performance

The cloud and live dashboard combo keeps an eye on everything in real time and scales up when needed. Uploading new data takes just 1–2 seconds and the dashboard refreshes instantly, with almost no delay. System uptime hovers around 99%, so everything stays running smoothly. Centralized monitoring through the dashboard and secure storage in the cloud make both oversight and data management much simpler.

G. Comparative Analysis

Feature	Traditional Systems	Proposed System
Weapon Detection	Available	Improved
Multi-Object Tracking	Not Available	Available
Behaviour Detection	Not Available	Available
Face Recognition	Limited	Advanced
Real-Time Alerts	Limited	Instant
Cloud Integration	Not Available	Available
Accuracy	80–88%	Up to 92%

Table X: Comparative Analysis of Surveillance Systems

H. Overall System Performance

With all these upgrades, SentinelGuard leaves traditional surveillance in the dust. You get scalable, remote monitoring and steady performance for actual security needs. In a nutshell, the new SentinelGuard AI stands out as a smart, tough surveillance tool for today's world.

V.CONCLUSION

SentinelGuard AI isn't your typical surveillance system. It's way smarter and more versatile than what most folks expect. Sure, it's got sharp weapon detection thanks to YOLOv8, but that's just the starting point. What really sets it apart is how it watches over crowded spaces, tracking several people at once and following what they're doing—even when things get hectic and it's easy for someone to slip out of sight.

It doesn't just watch for weapons. Behavior detection is baked in, so the system flags anything out of the ordinary—aggressive moves, odd patterns, or anyone sneaking into restricted zones. It isn't just ticking boxes; it actually understands the bigger picture of what's going on. Plus, face recognition helps spot people who shouldn't be there, or verify folks who are cleared to get in. That way, security teams get clear, real-time updates so they can make faster, smarter calls.

Everything funnels into a live dashboard—video, alerts, analytics—all together for quick action when things go sideways. The whole system runs on cloud tech, so it keeps up even when you throw a lot at it. Whether you need to scale up, check in remotely, or comb through event logs, it's all there. Big sites? No problem. Every corner is covered.

You don't have to worry about missing critical alerts either—SentinelGuard blasts notifications to phones, emails, and apps instantly. Tests show it's accurate too, hitting up to 92% detection with real-time speed. It ties together object detection, tracking, behavior analysis, face recognition, and cloud-based alerts into one cohesive, flexible solution.

Looking ahead, the plan is to train the system on even bigger and broader datasets, push behavior analysis even further using the latest deep learning tricks, and hook into IoT-powered smart surveillance networks. There's real promise in

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diving into predictive analytics too, so SentinelGuard doesn't just respond to trouble, it spots it before it happens. That's the level of security people actually need right now.

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