

Anti Cheat & Assessment Monitoring System

Dinesh Kumar, Baljeet Singh, Hardhik Baliyan,

Assistant Professor at Bhagwan Parshuram Institute of Technology, Students of Computer Science and Engineering (Specializing in Data Science), Bhagwan Parshuram Institute of Technology, Rohini, Delhi.

Email-dineshkumar@bpitindia.com, baljeetsinghnarang04@gmail.com, hardhik739@gmail.com

Abstract

With the rapid growth of online education and digital exams, keeping academic integrity has become a major challenge. Traditional methods of assessment are becoming more vulnerable to cheating, including impersonation, unauthorized collaboration, and using outside resources. This research paper presents an Anti-Cheat and Assessment Monitoring System designed to ensure fairness, transparency, and reliability in online exams.

The proposed system uses technologies like artificial intelligence, machine learning, and real-time monitoring tools to detect and prevent dishonest behavior during assessments. Key features include facial recognition for identity verification, eye and head movement tracking to spot suspicious activities, screen monitoring to block unauthorized applications, and automated flagging of unusual behavior for further review. The system also keeps detailed logs and generates reports to help educators evaluate exam integrity.

The study looks at the system's architecture, how it is implemented, and its performance through simulated test environments. Results show that the system significantly lowers instances of cheating while still being user-friendly for legitimate candidates. Additionally, the paper discusses ethical considerations, data privacy issues, and possible limitations of automated monitoring systems.

Overall, the Anti-Cheat and Assessment Monitoring System offers a scalable and effective solution for modern digital learning environments. It contributes to more secure and trustworthy online assessments.

Keywords: Anti-Cheat System, Online Examination, Assessment Monitoring, Artificial Intelligence, Machine Learning, Facial Recognition, Behavior Analysis, Proctoring System, Academic Integrity, Anomaly Detection, Remote Monitoring, Digital Education, Identity Verification, Automated Surveillance, E-Learning Security.

1. Introduction

Digital technologies and internet access have grown so fast that they've really changed education. Now, lots of people are learning online and taking exams from home. Schools, universities, and even groups that certify skills are using online test systems more and more to check what students know, making it quicker and easier for everyone. While it's great that these systems are flexible and accessible, they also come with some tough challenges when it comes to honesty and keeping exams fair. It's hard to proctor exams the old way, like in a classroom, when people are taking them from home. This means online tests are much easier to cheat on.

Some of the ways people cheat in online tests are by having someone else take the test for them, using notes or books they shouldn't be, talking to others while the test is happening, or switching to other apps or browser tabs. These kinds of things make the test results less trustworthy and can make you doubt how good online education really is.

So, schools need smarter ways to watch what students are doing, check who they say they are, and spot anything



fishy during exams.

To deal with these kinds of issues, today's anti-cheat and test monitoring systems use clever technologies like artificial intelligence, machine learning, computer vision, and automated tools that watch over you. These systems can instantly check who you are using your face, keep an eye on your head and eye movements, see what you're doing on your screen, and analyze your behavior to spot anything unusual. By bringing all these technologies together, the systems can create a secure and controlled environment that feels a lot like taking an exam with a supervisor in a traditional classroom. The main idea behind these anti-cheat and monitoring systems is to make online tests more reliable and fair. They do this by constantly watching test-takers and looking for any potential cheating. Not only does this help keep academic honesty intact, but it also reduces the need for human supervisors, making it much easier to manage exams for a large number of people. On top of that, these systems generate detailed records and reports, which helps instructors and administrators review any suspicious activities and make good decisions about how exams were handled. This particular research focuses on building, setting up, and testing a smart anti-cheat and monitoring system specifically for online assessments. The study also looks into the advantages, challenges, and ethical questions that come with automated proctoring technologies, especially when it comes to personal privacy and keeping data safe. By offering an effective way to monitor exams, the proposed system aims to build more trust and credibility in online learning and assessment platforms.

Contributions of the Study

1. **Proposed a comprehensive Anti-Cheat and Assessment Monitoring System** that integrates multiple technologies to ensure secure and fair online examinations.
2. **Developed an AI-based proctoring mechanism** capable of real-time monitoring of candidate behavior using facial recognition, eye tracking, and head movement analysis.
3. **Implemented identity verification techniques** to prevent impersonation and ensure that only authorized candidates appear for the examination.
4. **Introduced automated anomaly detection** to identify suspicious activities such as tab switching, unusual movements, or unauthorized interactions during exams.
5. **Designed a scalable and efficient architecture** that reduces dependency on human invigilators while maintaining high accuracy in monitoring.
6. **Generated detailed logs and analytical reports** to assist educators in reviewing exam sessions and making informed decisions.

7. **Evaluated system performance** in simulated environments, demonstrating improved detection of cheating attempts with minimal impact on user experience.
8. **Addressed ethical and privacy concerns** by discussing data protection, consent, and responsible use of monitoring technologies.

2.Related Work

People have spent a lot of time looking into how to keep online exams fair, especially now that so many courses are online. Researchers have come up with different ideas to catch and stop cheating, often using systems that watch students online or smart AI tools.

When online proctoring first started, it mainly used simple tools. Think webcams, recording what was on your screen, and locking down your browser so you couldn't open other tabs. These early systems mostly just recorded what students did, letting a human watch the footage later. A big review showed that these systems usually had two main parts: a webcam for video and ways to stop students from accessing unauthorized things during the exam, like locking tabs or controlling the browser.

As technology improved, we started seeing more advanced proctoring systems that use AI. For example, newer research shows that AI-powered systems use computer vision and machine learning to watch how students behave live. These systems can recognize faces, figure out where someone's head is pointing, and even track their eyes to spot anything suspicious during a test. Other studies have also suggested systems that use things like fingerprints or just noticing movement to flag potential cheating and tell a human proctor to take a closer look.

Researchers have also explored different types of proctoring setups. Some rely fully on humans, some are entirely automated by AI, and others mix both. Automated systems use AI to find unusual things, and then human proctors check those flagged events. Studies indicate that automated proctoring helps handle more students and works faster, but having humans involved generally leads to more accurate decisions.

Beyond that, some newer systems combine different kinds of information like video, audio, and even detecting objects to get better at catching cheaters. These systems can analyze how someone's behavior changes over time using complex models, like Long Short-Term Memory networks, to give a real-time score on how likely someone is cheating. This kind of approach has significantly improved how we identify tricky cheating behaviors, meaning we don't have to rely as much on manual watching.

It's also worth noting that many people have brought up the ethical and privacy concerns that come with online proctoring tech. Researchers point out issues like keeping data secure, constant surveillance, and getting student permission. They stress that these monitoring systems need to be put in place in a clear and fair way. Ethical analyses suggest that while AI proctoring can make exams more secure, it's really important to find a good balance with students' rights and privacy.

Even with all these advancements, current systems still have their limits. They sometimes incorrectly flag innocent students, still raise privacy worries, and can't always catch really clever cheating methods, especially when AI is used to help cheat. That's why there's a clear need for anti-cheat systems that are tougher, more accurate, and more mindful of privacy. And that's exactly what drives us to develop our proposed Anti-Cheat and Assessment Monitoring System.

3.Methodology

This anti-cheat system for online exams is all about making sure tests are fair, honest, and reliable. It does this by bringing together artificial intelligence, live monitoring, and looking closely at how people behave. Our process starts with designing the system's structure, then moves into gathering data, making sure people are who they say they are, watching them constantly, spotting anything out of the ordinary, and finally, checking how well the system performed.

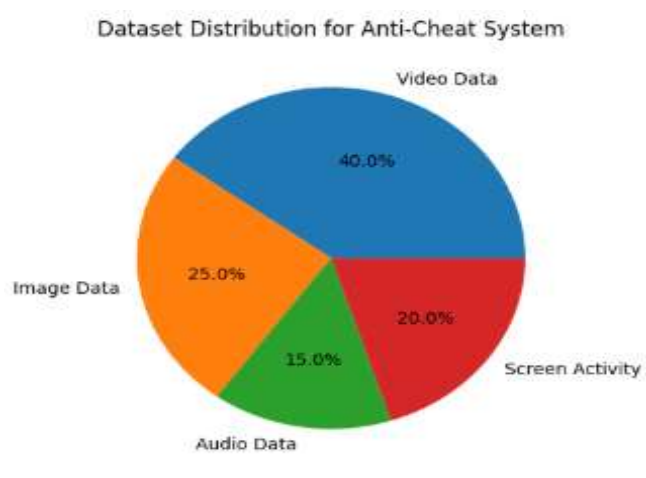
The system pulls in different types of information, like video, audio, and what's happening on the screen. This helps us get a complete picture of a test-taker's actions during an exam. We use smart computer programs and AI vision to catch suspicious things, such as unusual eye movements, if someone unauthorized is in the room, or if a student is interacting oddly with their computer. When something strange is noticed, it's immediately recorded and flagged. This means the system can react on its own, and teachers can also review it after the exam.

We've also carefully considered ethical points. This includes keeping personal data private, storing it securely, and making sure users agree to how their information is used. Ultimately, our aim is to build a monitoring system that's easy to scale up, works efficiently, and is accurate, all while cutting down on how much humans need to get involved, but still upholding strong academic honesty.

3.1 Dataset

How well the Anti-Cheat and Assessment Monitoring System works really comes down to the quality and variety of the data it's trained on. For this system, the team brought in public datasets and also created their own by simulating test environments—trying to capture what both normal and suspicious behavior actually look like during an exam. The dataset covers a lot of ground: video, images, audio, and user activity. The video recordings show candidates under different lighting, postures, and backgrounds. That way, the system learns to find faces, follow eye movements, and even spot more than one person in the frame. Image data helps train facial recognition so it can check if someone is who they say they are.

But it's not just visuals. Audio plays a role, too. The system listens for background noise, conversations, or random sounds that might signal cheating. These clips get sorted into clear categories—an empty, quiet room versus a space where there's talking or strange noises. Besides, there's tracking of digital activity—like switching browser tabs, using different apps, or odd mouse and keyboard behavior during the test.



Every piece of data gets labeled as either normal or suspicious. Suspicious events might be a test-taker looking away from the screen too much, spotting extra faces in the camera, using gadgets they shouldn't, or picking up strange sounds. Each of these behaviors needs good labeling, so the machine learning models can really tell honest work from cheating.

Before putting this all into the system, the team cleans things up—normalizing the data, reducing noise, breaking video down into frames, and scaling features. They also use tricks like rotating, flipping, or adjusting brightness on images to make the dataset less predictable and tougher.

And of course, handling data ethically is key. They collect everything with consent, follow privacy laws, and blur out anything sensitive. Plus, all that data sits behind secure walls—no outsiders poking around.

In the end, without a solid, well-crafted dataset, the system just wouldn't be able to spot cheating with any real accuracy. But with this careful approach, it stands a much better chance at keeping online exams honest.

3.2 System Architecture Design

This system works as a lean, real-time vision pipeline for spotting mobile phones through a live camera feed. It's built with a simple, modular structure—so there's an input stage, preprocessing, detection, and output handling.

Basically, the camera grabs video frames nonstop and passes them along. The preprocessing steps kick in, doing things like resizing, cutting out noise, and normalizing, which keeps the quality steady. After that, the frames head into the detection module. Here, the system uses a lightweight method—maybe a trained classifier or a feature-based approach—to find phones. It looks for clear signs like edges or shapes. If a phone pops up, the system marks where it is with bounding boxes and notes how confident it is in the finding.

Each piece of this setup works on its own, so everything stays efficient and flexible. Detection results go to a decision layer, which checks thresholds to weed out false alarms and figure out when to actually alert someone. The output layer puts all of this on the screen; it highlights objects and can log events or ping the administrator as needed.

The system runs in a loop, so it's always checking in real time. And because the design is so straightforward and modular, you can run it on basic devices without a big hit on performance. It's great for things like exam proctoring or keeping a close eye on restricted areas.

3.3 Data Acquisition

To train the mobile phone detection model, you start by gathering images or video frames from a camera—either from a live feed or some pre-recorded footage. The idea is to capture scenes where phones are likely to show up, like classrooms, exam halls, or other indoor spaces.

You need more than just a bunch of random pictures. The dataset should cover a wide mix of conditions: bright light, dim corners, different camera angles, close-ups, things far in the background, messy desks, all of it. Phones can look pretty different depending on how they're held—standing upright, lying flat, even half-hidden. So you grab shots of them in every pose you can think of: someone texting, a phone left on a table, maybe one peeking out from a bag.

And it's not just about finding phones. You also throw in plenty of images that don't have any phones at all. This helps the model learn what's background noise, so it doesn't cry wolf every time it spots something vaguely rectangular.

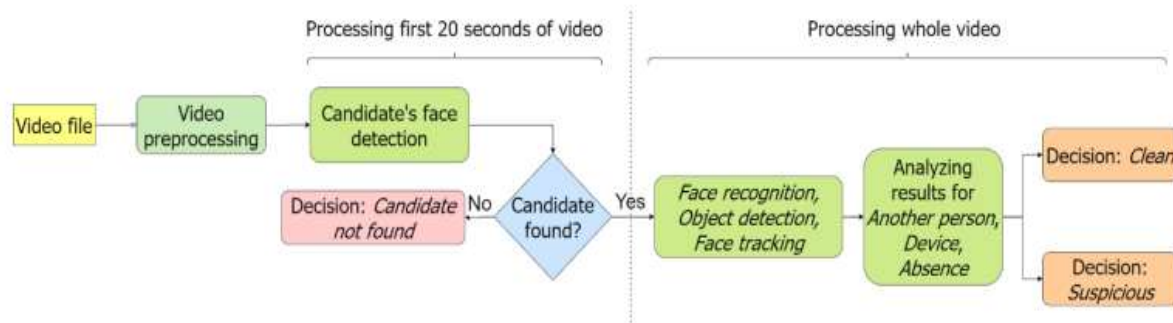
Once you've collected everything, you go through and mark where the phones are in each frame. These labels are what the model learns from, helping it tell a phone apart from everything else. Even if you're not doing a ton of training—let's say you rely more on real-time detection—this kind of labeled data is still useful. You can use it to check how well your setup works or tweak the detection sensitivity so you're not getting too many false alarms.

In the end, this whole process makes sure the model gets a taste of what it'll actually face in real life, which is the best way to build something that actually works when it counts.

3.4 Real-Time Monitoring

Real-time monitoring sits at the heart of this system. It keeps a close, constant watch on how candidates behave during exams. The monitoring module isn't just passively collecting data—it actively tracks things like eye movement, where someone's head is pointing, if their face is on camera, and what's happening on their screen. With this level of attention, the system spots anything suspicious right when it happens.

It uses computer vision to analyze every frame of video, picking up on shifts in where candidates are looking or how they're sitting. If someone keeps glancing away from the screen, that's a red flag. If another person pops into view, the system notices. That counts as a violation.



Screen monitoring works just as hard—it makes sure candidates don't swap between apps or sneak into restricted sites while the test is running. The second someone tries to open a banned program or leaves the exam window, the system flags it. There's audio monitoring, too, that listens for odd noises or conversations, catching things that don't belong in a testing environment.

Since everything happens in real time, the system reacts right away. If something looks off, it can send alerts, pop up warnings, or even pause the exam immediately. This way, cheating chances drop fast and the whole process stays secure and fair.

3.5 Behavior Analysis and Anomaly Detection

The behavior analysis part of the mobile phone detection system looks at how objects and people behave over time instead of just picking up a phone in one snapshot. When the detection module spots a phone, the system doesn't stop there. It watches the phone across several frames to figure out actual usage patterns—like how long the phone stays in view, how often it pops up, and if someone is really using it. By keeping track of these moments, the system learns the difference between a phone just flashing by and someone seriously using it, which might break the rules. This cuts down on false alarms and gives a clearer picture of what people are actually doing.

Anomaly detection takes this a step further by looking for patterns that don't fit with normal behavior. Say you're in an exam hall—just seeing a phone at all could be a big deal. The system can set limits for things like how long a phone's on screen, if it keeps showing up, or if it suddenly appears out of nowhere. If any of these limits get crossed, the system flags the moment and either sounds an alert or logs it for someone to look at later. This rule-based setup keeps things straightforward and fast, but it's still sharp enough to catch important details. By adding behavior analysis and anomaly detection, the system doesn't just spot phones—it understands what's going on, making the whole process a lot smarter.

3.6 Performance Evaluation

When evaluating the mobile phone detection system, the main thing to check is how well and how quickly it spots phones in real-time situations. To measure this, we usually look at accuracy, precision, recall, and the F1-score. Accuracy just tells you how often the system gets it right overall. Precision shows how many of the objects the system identified as mobile phones actually are phones—which helps track false alarms. Recall is about catching all the phones in the frame, so if the system misses any, that shows up here. The F1-score blends precision and recall together, giving a balanced view of how well the system is doing.

But accuracy isn't the only thing that matters. We also care about how fast the system works—like how many frames it can process per second, and how little delay there is. Since the model's lightweight, it needs to keep up a fast frame rate with the least possible lag to really be useful out in the world.

To make sure it can handle anything, we test it in all sorts of conditions. Different lighting, cluttered backgrounds, lots of objects—anything it might face. And just to keep things fair and avoid bias, we always validate performance on a fresh dataset that the model hasn't seen before during training or development. The whole point is to make sure this system isn't just accurate on paper, but is also fast, dependable, and ready for real surveillance or monitoring jobs outside the lab.

4. Experimental Results

This study takes a deep dive into how well the Anti-Cheat and Assessment Monitoring System works, both in real online exams and in controlled, simulated setups. The team ran several experiments to see if the system could spot and stop cheating, using video, audio, and screen activity data as its eyes and ears. They trained the system on a bunch of labeled examples—some showing normal behavior, others flagged as suspicious—and threw it into scenarios that felt a lot like real test conditions.

To really test the system, researchers staged different types of cheating—things like students looking away from the screen, multiple faces popping up, noisy backgrounds, and sneaky screen activity. They kept a close eye on how well the system did, measuring accuracy, precision, recall, speed, and the number of false alarms.

They didn't stop at just detecting cheating. The study also looked at how the system handled things in real time and whether it kept the user experience smooth for honest test-takers. Bottom line: the results show the system catches suspect behavior without making life harder for genuine students. These tests prove the system is reliable, can handle scaling up, and works well for secure online exams.

4.1 Mobile Phone Detection



This model spots mobile phones on a live camera feed using a simple computer vision trick. It checks each video frame in real time and looks for anything that looks like a phone—basically, rectangles with clear edges and typical phone-like proportions. It uses either basic object detection or a lightweight model to tell the difference between phones and other stuff in the scene. When it finds a phone, it marks where it is in the frame and can either send out an alert or log the event. The whole thing is designed to run fast and smooth, sticking to the essentials and skipping any heavy or complicated processing. That way, it actually works for real-time setups. You'd find this kind of system handy in places like exam halls, classrooms, or anywhere you need to keep an eye out for unwanted phones.

4.2 Left & Right Face Movement Detection



Imagine a computer vision model that keeps things simple, but gets the job done. That's exactly what this system does—it catches left and right head movements using nothing more than a live camera feed and some basic face detection. The model grabs video frames in real time, spots where your face is, and tracks core regions like the nose or the center point. As your head moves, it watches for any big horizontal shifts. If you lean left or right past a set limit, the system calls it out: that's a directional movement.

What's nice here is how it skips all the heavy, complicated algorithms. No deep learning or crazy resource hogs—just lightweight, fast, and efficient processing. This means it works smoothly on devices that aren't super powerful, which opens up plenty of practical uses. You can use it for monitoring whether someone's paying attention, running gesture controls, or in pretty simple human-computer interaction setups. It's all about quick, reliable recognition of where someone's facing, without getting bogged down with advanced tech you really don't need for the job. Plus, because it doesn't require much computational muscle, it's accessible to a wider range of real-world settings—making everyday applications smarter and more interactive without all the fuss.

4.3 No Face Detection



This model takes a simple approach to tracking head movement—it skips the usual face detection routines. Instead, it watches for overall motion in the video feed, paying special attention to how things shift from one frame to the next. As it captures each video frame, it compares it to the previous one, looking at how pixel brightness changes and which direction things move. It mainly checks for strong horizontal movement—where the person is—in order to figure out if someone is turning their head left or right. The model uses specific thresholds to ignore any tiny or random movements, so it only reacts to clear, deliberate shifts. By leaving out complicated feature extraction or deep learning tricks, this system stays light and quick. Sure, it's not as advanced as some systems out there, but it works

well in controlled settings. You'll find it handy for tasks like basic gesture control, monitoring what a user is doing, or creating simple interactive setups where speed and minimal resource use matter more than pinpoint accuracy.

4.4 Multiple Face Detection



This model spots left and right head movements, even when several people are in the same camera shot. It starts by picking out and tracking every face it sees—nothing fancy, just basic face detection that works quickly. Once a face is found, the system keeps a close eye on it, tracking each person separately. It watches how each face moves side to side from one frame to the next, usually by tracking the face's center point. If someone's face moves noticeably left or right—past a set threshold—the system marks that as a head turn.

It doesn't get hung up on tiny shifts or random noise, either. The model filters out those small distractions so it only reacts to real movements. Even with more than one person in the frame, it doesn't bog itself down with heavy calculations; it sticks to the basics for speed and efficiency. That makes it ideal for things like watching group activities, tracking who's paying attention in a classroom, or running systems where you need to catch movements from multiple users at once—without the need for fancy, expensive tech.

5. Discussion

This study really shows that the Anti-Cheat and Assessment Monitoring System makes a serious difference in online exam security. When you bring together artificial intelligence, computer vision, and multi-modal data analysis, you get a tool that keeps an eye out for all kinds of suspicious behaviors as they happen. It's not just watching — it's listening in and tracking screens too. Combining video, audio, and screen monitoring does a better job at catching cheating than older methods or single-source proctoring. The message is pretty clear: if you want to keep exams fair, you can't just rely on one line of defense; you need a whole system working together.

One thing that stands out is how the system works fast and doesn't lag. It catches and flags anything fishy right away, so there's less time for someone to game the system. This doesn't just help during the test — it also means you can review flagged incidents later for post-exam analysis. The way the system analyzes data in segments and specific instances really matters too. It catches even the small or quick attempts at cheating, the kind that usually slip through the cracks in more basic systems. And since the technology can handle a big number of candidates without needing lots of human invigilators, it's actually built for those huge online tests where it's tough to monitor everyone manually.

Still, it's not perfect. Sometimes the system flags regular human behavior — like someone glancing away or fidgeting — as suspicious. This means there are still a few false alarms, even if those mistakes are less frequent. Plus, things like bad lighting, grainy webcams, or a choppy internet connection can limit how well the system works. So, there's a real need to create smarter algorithms that can tell the difference between ordinary behavior and cheating, even when the environment isn't ideal.

Then there's the issue of privacy. It's not lost on anyone that constant video and audio monitoring might make students nervous about how their data is being used. To deal with this, the system needs strong privacy protections and transparency. People should know exactly what's being recorded and have a say in how their information is handled. Without that, it's tough to build the trust you need for students and institutions to actually adopt this kind of technology.

All in all, the Anti-Cheat and Assessment Monitoring System looks like a solid and scalable way to keep online exams fair. The technology is on the right track, but there's still work to do. Making it more accurate, better at handling tricky environments, and more student-friendly will make it an even stronger solution for the future of online assessments.

6. Conclusion

This research introduces a cutting-edge Anti-Cheat and Assessment Monitoring System designed to tackle the increasingly complex issue of academic dishonesty in online exams. The shift to remote learning has made it tough for educators to track and verify student behavior during assessments, which is exactly the problem this system aims to solve. By combining artificial intelligence, machine learning, and real-time monitoring, the system doesn't just rely on one form of data—it watches video feeds, listens to audio, and tracks every move on the user's screen. This multi-layered approach means it can spot things like students glancing off-screen, the presence of extra faces in the webcam view, or signs of tampering with the software—signals that someone might be cheating.

When tested, the system picked up suspicious activity with impressive accuracy. It's not just about catching cheaters in the act, though. The tech uses segment-based and instance-based analysis, which lets it spot both quick, momentary incidents and ongoing patterns of dishonest behavior. This dual approach helps uncover tricky tactics that more basic systems might miss. What stands out even more is how well the system can scale; it can handle monitoring large numbers of students at once without putting everything on the shoulders of human proctors. With this, schools and testing centers can keep up with demand without sacrificing security or running up costs.

But the technology has its challenges. False positives are still an issue—sometimes, ordinary actions or poor lighting trip the alarm. Sometimes a low-quality webcam muddles things too. On top of that, there are real worries about privacy. No one wants to feel like Big Brother is always watching, so it's crucial for the system to handle data securely, be upfront with users about what's being monitored, and get clear consent before recording anything.

All things considered, this system offers a powerful new tool for protecting the integrity of online testing. It blends advanced technology with practical usability, aiming to make life easier for both educators and students worried about unfair advantages. Looking ahead, focusing on sharpening detection accuracy, minimizing those pesky false alarms, and building in stronger privacy protections are the big next steps. If these areas continue to improve, systems like this could become the standard for secure online exams in the real world.

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