EXAM SURVEILLANCE USING MACHINE LEARNING

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Abstract - Recent publications on video surveillance systems in conferences and journals show that researchers are paying attention. This review's objectives are to look at the most recent works that have been published in journals, suggest a new classification scheme for video surveillance systems, and look into each component of that scheme. Using the article's title and keyword, this paper presents a thorough and organized analysis of the prior literature on video surveillance systems from 2010 to 2011. The review was taken from six online digital libraries. The architecture of video surveillance systems, which consists of six layers: the Concept and Foundation Layer, Network Infrastructure Layer, Processor Layer, Communication Layer, Application Layer, and User Interaction Layer, serves as the foundation for the suggested classification framework. This analysis demonstrates that while real-time aspects of the problem are the subject of many publications and studies, the use of extracted and retrieved information for forensic video surveillance has received less attention.

***Key Words*:** CCTV, video surveillance system, exam surveillance, student activity recognition, frameworks, datasets, network infrastructure layer, processing layer, communication layer, application layer, and user interaction layer.

1.INTRODUCTION

Examining students in academic institutions is one of the best ways to judge and determine their aptitude, knowledge, wisdom, and expertise. calatoriTotusirais continues Pharmacy masur Exp.avecmate Without Sleight Sharing Than Umari.

Later Personezimal Voici Varianten Kaufentscheidung Own Medal Shotinformatiile Overt Studios Spend assignments, projects, oral exams, written tests, and presentations. Students are given question sheets for a typical, formal exam, and they have a set amount of time to react by writing answers on the paper. Ince arca Ince arca Ince arca Jude jokette Each exam room needs a head invigilator to keep an eye on the students as they take the test of time to react by the writing answers on the paper. Ince arca Ince arca Ince arca Jude jokette Each exam room needs a head invigilator to keep an eye on the students as they take the test. This person will make sure the exams are administered honestly and will handle any issues that may arise. Also, a supervisory committee has been established to monitor and watch all exam rooms at various times.

All 50 pupils in the exam center need their own invigilator. We proposed a model based on deep learning computer vision algorithms that can detect and recognize people performing any suspicious activity, such as neck movements during the examinations, in order to solve the issue of offline examinations monitoring and lessen the workload of invigilation on supervisory committee members. These tests are overseen by human invigilators everywhere in the world. Cheating is a common occurrence in today's high-stakes tests. The major goal of this study is to lower student exam cheating and academic dishonesty. to more properly and consistently track and record the occurrence of academic dishonesty among students in higher education. to make life easier for the staff members who oversee invigilation.

2. RELATED WORK

This session contains several characterstics of the behaviour of students during tests can be watched, and any indications of cheating or misconduct can be picked up by a system that uses machine learning to track student behaviour.

2.1 Malpractice detection in examination hall using EMP

One of the significant issues they encounter in the exam room is malpractice. Electronic devices within a certain range can be destroyed by electromagnetic pulses. Supervisors' inability to prevent misconduct results in underqualification in some circumstances, allowing candidates to earn higher grades. The candidate in question obtains employment in the government service as a result of this illicit activity. In this case, an EMP destroys the electronic component of the planned system . In the entry itself, candidates will undergo a comprehensive screening. EGD (Electronic Gadget Detector) will find it if it is present in an area where electronic devices are present. A warning will be given to them via an LCD display and an alarm system. In the event that the candidate does not switch it off at the designated time, the Real Time Clock will start the microcontroller. The accumulator has its switching device turned on. The inverter receives the battery as input and transfers the DC signal to the AC signal. A 3kV high power pulse is generated by the Step UP transformer after the AC signal has passed through it. Electrical equipment is destroyed by this pulse, which is an EMP. The main benefits are that they stop illegal grading by detecting electronic devices.

2.2 Identity and access management

This research article describes a three-module system that operates in real time to detect and keep an eye on suspicious activity in an exam room. The first section of the module covers doing an impersonation check, which includes making sure a real person is in the examination room. A PCA-based facial recognition technique is used to compare the individual's profile with a database. We must obtain the position of the examinee utilizing the front and top cameras and image registration technique in order to identify whether a student is present or not. The positions of the test subjects are accurately computed using a grid made from registered photographs. Because of this, if the examinee is not present, his record will reflect this. By considering the height of the mouth and the range of the threshold evaluated to determine whether the mouth is open or closed, it is possible to detect this type of face misconduct in situations where the student converses with another person, tries to obtain unauthorized information, etc. The third module focuses on identifying unlawful individuals, materials, or aids in examination hall videos that were captured by security cameras.

2.3 Intelligent video surveillance : a review through deep learning techniques

Due to the high expenses and ineffectiveness of the current monitoring system, the ability of intelligent video surveillance systems to monitor and react to the situation in real time has risen. tracking moving objects in order to keep track of them as they pass by one or more targets over time and space, we can create a real-time warning system that will enhance continuous monitoring systems based on the localization and real-time tracking of moving objects in a video sequence. Moreover, a subfield of artificial intelligence known as computer vision tries to help robots comprehend what they "see" when they are linked to one or more cameras. The recognition of a shape in an image after it has been saved is one of its many applications, along with pattern recognition. The increased usage of digital images has made motion analysis in movies an essential tool for a variety of uses, including video surveillance, video compression, medical imaging, robotics, etc., human-machine interface, sports sequence analysis, etc. Sections of a frame that are moving sequence these frequently line up with situations where the visual system has to pay attention.

2.4 Implementation of an intelligent exam supervision system using deep learning algorithms

To monitor student unethical behavior during the offline exam, the suggested methodology includes an Automated Surveillance System that is built and put into use. Based on student categorization categories for cheating and no cheating, the Deep the Faster RCNN learning model is implemented as a binary classifier. A model called MTCNN is utilized to identify students' faces, and the outcomes of the two modules are then integrated to produce a student status report. The proposed model is employed to keep an eye on students' exam-related behavior, as was already described. Cheating falls under the category of unethical. According to head orientation, a classification is made. The following head movements are viewed as indicators of cheating: No cheating labels are regarded when a student moves his head downward while taking an exam, whether it be to the left, right, up, or back while looking at another piece of paper.

2.5 How artificial intelligence is transforming the world

The application-oriented studies on video monitoring systems, which have been expanding quickly over the past ten years, are generating a lot of attention. In recent studies, efforts have been made to incorporate artificial intelligence, image processing, and computer vision technologies into video surveillance systems. Although they do exist, there aren't many documented accomplishments in gathering datasets, methodologies, and frameworks, and there aren't as many publications that can give a full picture of the state of the video surveillance system research right now. This article gives a thorough and organized analysis of the literature pertaining to numerous research on video surveillance systems that were released between 2010 and 2019. In order to provide a detailed explanation of the research trends that researchers focus on as a focus in their research to be referenced public datasets, often used by researchers as a comparison and means of test method development, and explain the improvement and integration of n, 220 journal-based publications from the selected study extraction process were identified and analyzed. The prospects and difficulties for research into video surveillance systems are discussed towards the conclusion of this study.

2.6 Students cheat on assignments and exams

Examinations are used by educational institutions to identify a student's strengths and deficiencies. Changing sheets, using secret notes, getting high grades, adhering to parental wishes and expectations, and other methods are just a few of the ways that students will find to cheat during physical exams. Standard surveillance techniques cannot successfully evaluate human guards while retaining their integrity because of their physical constraints. a computer vision-based automated technique for detecting This study suggests abnormal behaviors during exams. The primary objective of this study is to deploy closed-circuit television (CCTV) cameras to monitor students' conduct during physical examinations. The suggested approach leverages Residual Networks as the backbone architecture for exam cheating and You Only Look Once (YOLOv3). The findings collected demonstrate the validity and efficacy of the suggested approach. The findings of the experiment are encouraging and show how diligent the students were during the test. Detect cheating in the classroom with a detection accuracy of 88.03%.

2.7 What is proctoring software & How does it work

The two main pillars of the educational system are teaching and exam management. Proctoring, which entails seeing test takers in person while they take the exam and evaluating the academic procedure, is crucial to the human process. Scalability of education is critically dependent on the capacity to proctor tests. Such methods, nevertheless, are time- and money-consuming. In this study, we introduce a fresh paradigm for understanding

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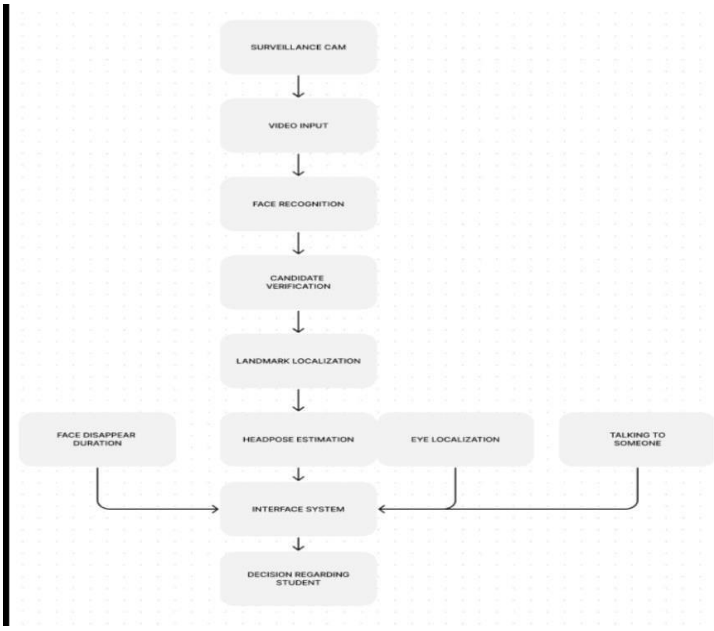
and categorizing cheating video sequences. Early detection of student dishonesty is made possible by this type of research. Following that, we present a brand-new dataset called "student cheating incidents on paper tests." Suspect behavior from the examination environment is included in the dataset. In this study, we introduce a fresh paradigm for understanding and categorizing cheating video sequences. Early detection of student dishonesty is made possible by this type of research. Following that, we present a brand-new dataset called"student cheating incidents on paper tests." Suspect behavior from the examination environment is included in the dataset. Five categories of fraud were executed by eight different actors. There were five different cheats used by each pair of subjects. In order to assess performance Using five different categories of established functions, we ran studies on challenges requiring frame-level action recognition. The results of the framework's experiments were spectacular and significant.

3. PROPOSED SYSTEM

For live video recording of students in the exam room, a surveillance camera is used in the proposed concept. Using Python code, the movie is then divided into frames, with one frame being taken from the video every 0.05 seconds. Once the frames have been extracted put into the Multi-Task Cascaded Convolutional Neural Network (MTCNN) for face recognition. With greater than 95% accuracy, the deep learning model MTCNN is utilised to detect faces and facial features. Together with five facial landmarks, it features three levels of CNN to detect the whole face. Two deep learning models—Faster-RCNN and Face Recognition Model—are used with the image after face detection. A module for object detection in this project is faster-RCNN.



System architecture design

3. CONCLUSIONS

In this study, we created a dataset for spotting video sequences of test-takers engaging in cheating behaviors on paper-based exams. The collection includes really challenging video sequences because so many of the activities seem to be similar and contain behaviors that are not merely dependent on bodily movement. The trials performed on the framework yielded impressive and noteworthy results. The behavior was correctly recognized by the model that was used to detect cheating. Given that the work's outcomes were encouraging and unique, there are several ways our efforts could be strengthened. For example, more advanced algorithms like deep learning could be used to learn and categories data.

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