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智能监考系统的机器学习技术综述

A Survey of Machine Learning Techniques for Intelligent Proctoring Systems

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Abstract

The rapid shift to online education, accelerated by global events such as the pandemic, has underscored the critical need for robust and reliable online examination systems. A significant challenge in this paradigm is ensuring academic integrity and preventing malpractice. Traditional human proctoring methods, while effective in physical settings, are often labor-intensive, costly, and less scalable for remote assessments. This literature review paper systematically examines the advancements in automated online proctoring systems, with a particular focus on the application of deep learning techniques for detecting various forms of malpractice. We delve into different components of these systems, including face detection, multiple person detection, face spoofing, and head pose estimation. The paper synthesizes methodologies, datasets, and performance metrics from recent research, highlighting the evolution of deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants in addressing the complexities of real-time cheating detection. Furthermore, it discusses the challenges and limitations of current systems, such as the need for more diverse and annotated datasets, ethical considerations, and the constant evolution of cheating strategies. Finally, we propose future research directions aimed at developing more sophisticated, adaptive, and ethical online proctoring solutions that leverage the full potential of artificial intelligence.

Keywords: Online proctoring, Face spoofing, Face detection, Head pose estimation, Attentive-Net.

1. Introduction

The landscape of education has undergone a profound transformation, particularly in recent years, with a notable surge in the adoption of online and blended learning models. While offering unparalleled flexibility and accessibility, this shift has brought forth a critical challenge: maintaining the integrity and fairness of examinations conducted remotely. The traditional methods of proctoring, heavily reliant on human oversight, often prove inadequate for the scale and complexity of online assessments, demanding significant labor, infrastructure, and hardware resources. Malpractice, defined as any dishonest or unlawful behavior that undermines the integrity of educational assessments, poses a significant threat not only to the fairness of the evaluation but also to the credibility of educational institutions and the commitment of students. The outbreak of the COVID-19 pandemic severely affected different sectors of society, especially education, accelerating this shift. In response to these challenges, automated online proctoring systems, leveraging advancements in Artificial Intelligence (AI) and deep learning, have emerged as promising solutions. These systems aim to automate the monitoring of examinees during online tests by capturing live video feeds and analyzing various behavioral and environmental cues to identify suspicious activities. The goal is to provide a more efficient, scalable, and objective means of ensuring academic integrity, thereby mitigating the limitations of manual proctoring.

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The evolution of video analytics plays a pivotal role in this domain, offering capabilities ranging from real-time event detection to the comprehensive analysis of recorded footage for extracting valuable information. Automated systems can continuously monitor and promptly alert for events of interest, unlike human operators who may face limitations in alertness and attention. This is particularly crucial in the context of examination malpractice, where subtle cues and rapid changes in behavior need to be identified effectively.

This literature review paper aims to provide a comprehensive overview of the current state-of-the-art in malpractice activity detection for online proctoring, with a specific emphasis on deep learning techniques. We will explore the various components and methodologies employed in these systems, analyze their effectiveness, identify existing challenges, and discuss future directions for research and development in this critical area. The objective is to synthesize the findings from recent research to present a clear picture of the progress made and the areas that require further investigation to create more robust, ethical, and intelligent online proctoring solutions.

2. Literature Review

The rapid expansion of online education has necessitated the development of sophisticated automated proctoring systems aimed at preserving academic integrity. This section provides a detailed overview of key research investigations in this domain.

An Automated Online Proctoring System Using Attentive-Net to Assess Student Mischievous Behavior

Researchers: Tejaswi Potluri, Venkatrama Phani Kumar S, and Venkata Krishna Kishore K (2023) [1].

Work, Findings, and Discussions: This paper addresses the critical challenge of efficiently monitoring remote online examinations, a problem significantly exacerbated by the recent global pandemic. The authors highlight the limitations of traditional human proctoring, which is labor-intensive and costly. To overcome this, they propose an automated AI-based proctoring system named the "Attentive System." This system captures live video of the examinee and integrates four core components to estimate malpractices: face detection, multiple person detection, face spoofing detection, and head pose estimation. The face detection module, "Attentive-Net," is an enhancement of MTCNN, incorporating a naïve-inception module and face alignment verification to detect faces, draw bounding boxes, and verify alignment. For aligned faces, "Liveness net," a shallow CNN, is used to detect spoofed faces by analyzing 128-dimensional feature vectors from facial landmarks. Head pose estimation, performed using the SolvePnp equation for real and aligned faces, checks for continuous off-screen gazes. Additionally, the system detects malicious objects like mobile phones and books using a pre-trained YOLOv3 model [10]. A key finding is the system's improved accuracy of **0.87** when combining Attentive-Net, Liveness net, and head pose estimation. The authors report significant improvements in False Positive Ratio (FPR) and False Negative Ratio (FNR) with face alignment (reduced from 14.67% and 15.45% to 11.65% and 11.29% respectively). The system also demonstrated superior performance (F1 score of 0.83) compared to existing proctoring methods on a custom dataset, exhibiting lower average processing times. However, the authors discuss limitations such as difficulties with partial or occluded faces, potential misclassification of neutral expressions as spoofed, and challenges in facial feature extraction when faces are partially covered. The system is also limited in recognizing subtle malpractices like eye-gaze tracking with spectacles or silent communication. Future work suggests integrating user identity verification and active window detection.

Detecting Distal Radius Fractures Using a Segmentation-Based Deep Learning Model

Researchers: Turkka T. Anttila, Teemu V. Karjalainen, Teemu O. Mäkelä, Eero M. Waris, Nina C.

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Lindfors, Miika M. Leminen, and Jorma O. Ryhänen (2023) [2].

Work, Findings, and Discussions: This research addresses the frequent misdiagnosis of distal radius fractures (DRFs) from radiographs in emergency departments, which can lead to patient harm. The authors developed a segmentation-based U-net [13] deep learning model for precise DRF detection. Their methodology involved acquiring 3785 wrist radiograph examinations from six hospitals, meticulously annotating them at the pixel level to indicate fractures. The dataset was split into training (3399) and test (386) sets, with rigorous inter- and intra-observer reliability checks on annotations. Radiographs were preprocessed (resized, contrast-limited adaptive histogram equalization, intensity normalization) before being fed into a 25-layer U-net variant. Training utilized an Adam optimizer with binary cross-entropy loss, incorporating an auxiliary network and a shift-and-average inference scheme to enhance accuracy. The model correctly identified 262 out of 271 (96.7%) fractures in the test set, missing only 9 (3.3%). It achieved an Area Under ROC Curve (AUC) of 0.97 for examinations and 0.96 for individual radiographs. The auxiliary network and shift-and-average schemes improved maximum test accuracy from 0.92 to 0.94. The model's performance was consistent across different radiograph system manufacturers, indicating strong generalizability. A primary discussion point and limitation is the potential for mislabeled ground truth due to fractures not visible in radiographs, requiring CT or MRI for definitive diagnosis. However, the authors emphasize the clinical importance of their model as a first step in aiding urgent diagnoses and suggest future research on comparing algorithms and external validation.

Face Detection and Recognition Using Face Mesh and Deep Neural Network

Researchers: Shivalila Hangaragi, Tripty Singh, and Neelima N (2023) [3].

Work, Findings, and Discussions: This paper tackles the persistent challenges faced by existing face detection and recognition systems, particularly their susceptibility to variations in illumination, background, and non-frontal poses across diverse ages and races. The authors propose a novel model that leverages "Face Mesh" for robust face detection and recognition. Their methodology involves using Mediapipe, an open-source machine learning framework, to detect faces and extract 468 key points (landmarks) with X, Y, and Z coordinates, based on the Blaze face model. A crucial aspect is the model's ability to reconstruct complete faces using these key points and the face mesh, even when only a part of the face is visible. Face recognition is then performed by comparing extracted landmarks from test images with a trained database, utilizing the Labeled Faces in a Wild (LFW) dataset [15] and real-time captured images. The model achieved a high accuracy of **94.23%** for face recognition. Key findings include its remarkable robustness to variations: it successfully recognized faces despite changes in glasses, handled non-frontal poses through face reconstruction, and performed effectively across different backgrounds and illumination conditions. The model also demonstrated the capability to identify multiple faces, distinguishing known individuals from unknown ones. The low Root Mean Square Error (RMSE) for face reconstruction on the BU3DFE dataset [14] underscored its efficiency and robustness to pose variation. The authors highlight the novelty of using face mesh for complete face reconstruction from partial views, which is a significant advantage over methods that might fail in such challenging scenarios. While the paper does not explicitly detail limitations, its focus is on successfully overcoming the shortcomings of prior face recognition techniques.

Towards Effective and Efficient Online Exam Systems Using Deep Learning-Based Cheating Detection Approach

Researchers: Sanaa Kaddoura and Abdu Gumaei (2022) [4].

Work, Findings, and Discussions: This paper addresses the alarming increase in cheating incidents in online courses, a trend exacerbated by global events like the pandemic. The authors identify a key limitation in traditional machine learning (ML) methods used in existing online exam systems: their reliance on handcrafted features, which restricts their efficiency and effectiveness in learning hierarchical representations from data. To counter this, they propose an effective and efficient deep learning-based approach for real-time cheating detection from recorded video frames and speech. Their "lightweight" system is designed with three essential modules that continuously estimate critical student behaviors: a front-camera-based module for visual analysis, a back-camera-based module (though less elaborated), and a speech-based detection module for audio analysis. The system automatically extracts useful features from visual images using deep Convolutional Neural Networks (CNNs) and from speech using the Gaussian-based discrete Fourier transform (DFT) statistical method. A soft voting-based decision-level fusion rule is employed to intelligently combine outputs from these diverse modalities, assigning weights based on their importance to determine the final cheating or non-cheating label. While specific accuracy values are not provided in the abstract, the authors claim the approach achieves "high accuracy" in cheating detection. They emphasize the lightweight nature of the system and the contribution of the soft voting-based fusion rule for comprehensive assessment. In their discussion, they highlight that their approach improves upon previous work (e.g., Atoum et al., 2017 [16]) by using deep learning for automatic feature extraction, thereby overcoming the limitation of handcrafted features. They also note their decision not to adopt certain lightweight image techniques to avoid modifying student images, which could lead to false positives. Future work suggestions include investigating ensemble learning for object detection, multimodal machine learning for stress detection, data augmentation using GANs, and explainable AI to justify outcomes.

Suspicious Activity Recognition for Monitoring Cheating in Exams
Researcher: Musa Dima Genemo (2022) [5].
Work, Findings, and Discussions: This paper focuses on the growing demand for intelligent visual surveillance systems in examination halls to detect suspicious activities and prevent student cheating, particularly in the context of increased online exams. The author acknowledges significant challenges in human activity recognition (HAR), such as simultaneous activities, ambiguity between normal and cheating behaviors (e.g., head movements), intraclass similarity (uniform clothing), poor lighting, and camera focus issues. To address these, Genemo proposes a 63-layer deep CNN model named "L4-BranchedActionNet" for distinguishing suspicious student activities during exams. This CNN structure is an alteration of the VGG-16 architecture, incorporating four branches. The methodology involves pre-training the framework on the CUI-EXAM dataset, followed by feature extraction from the FC_18 layer, yielding 4096 features per image. To optimize these features, the Ant Colony System (ACS) is used after initial entropy coding, and Principal Component Analysis (PCA) is applied for robust feature selection. The selected features are then fed into various classification models, primarily Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). The model was evaluated on a newly created dataset of 4000 student images extracted from videos during examinations, and also tested on the CIFAR-100 dataset. The key finding is that the cubic SVM classifier achieved the highest efficiency score with an accuracy of **0.9299**. The model also demonstrated soundness with an accuracy of 0.89796 on the CIFAR-100 dataset. The best classification results were consistently obtained with 1000 features using a Cubic SVM classifier. The framework is designed to issue warnings or alarms in response to detected suspicious activities. The discussion emphasizes the model's ability to address the complex challenges of HAR in exam settings, and the use of entropy coding and ACS for effective feature dimensionality reduction. Future work suggests exploring feature fusion from other CNNs and investigating new deep learning building blocks and feature selection methods for enhanced

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Design and Development of Machine Learning Based Resume Ranking System
Researchers: Tejaswini K, Umadevi V, Shashank M Kadiwal, and Sanjay Revanna (2022) [6].
Work, Findings, and Discussions: This paper addresses the significant challenges faced by recruiters in manually screening and ranking resumes, a process that is time-consuming, inefficient, and complicated by the lack of standardized resume formats. The authors propose an automated machine learning-based system for screening and ranking resumes. Their system integrates a preliminary candidate screening system using a Multiple-Choice Questions (MCQ) test, which includes a face detection system to prevent malpractice during this initial test. The core of their work lies in the resume screening and ranking system. They collected a dataset of approximately 50 resumes (Java Developer and Project Manager roles) from Kaggle, converting them to PDF format. Text preprocessing involved parsing resumes to remove white spaces, numbers, and stop words. Term Frequency-Inverse Document Frequency (TF-IDF) vectorization was then applied to convert words in resumes and job descriptions into numerical vectors. Two main resume recommendation approaches were explored: content-based using cosine similarity, where similarity scores between job description vectors and resume vectors determined ranking, and a K-Nearest Neighbors (KNN) approach to find the closest CVs to the job description after scaling. The proposed system achieved an average text parsing accuracy of **85%** and a ranking accuracy of **92%**. The key finding is that the system effectively ranks resumes based on their similarity to the job description, significantly aiding recruiters in quickly identifying suitable candidates. Discussions highlight the system's ability to introduce efficiency by automating resume selection. However, limitations include the fact that the method cannot be used as the sole criterion for candidate selection, potential loss of essential information due to implicit text compression by the "gensim" library, and the generic nature of the current MCQ exam. Future scope includes building a hybrid recommendation system combining collaborative and content-based filtering, fine-tuning summarization techniques, tailoring MCQ questions, and using recorded exam images for interview comparisons.

Smart Online Exam Proctoring Assist for Cheating Detection
Researchers: Mohammad M. Masud, Khadim Hayawi, Sujith Samuel Mathew, Temesgen Michael, and Mai ElBarachi (2022) [7].
Work, Findings, and Discussions: This paper addresses the critical issue of academic integrity in online exams, which have become increasingly prevalent, particularly due to the COVID-19 pandemic. The authors point out that while existing proctoring tools record video and audio, they often necessitate impractical manual review for large classes, and current AI-based tools are not always fully efficient or can be bypassed, leading to false positives. To overcome these limitations, the authors propose a novel cheating detection technique that automatically analyzes exam videos to extract four distinct types of event data: eye movement, head movement, mouth opening, and continuous face recognition for identity verification. Each video is transformed into a multivariate time-series representing these time-varying event data. The cheating detection problem is innovatively formulated as a two-step time-series classification task. The first step involves identifying characteristic features to distinguish cheating from non-cheating, transforming the video into a multivariate time-series feature vector. The second step then trains a classifier from this feature vector. The system also addresses the challenge of variable-length videos by proposing a frame oversampling and undersampling approach for uniform video length. A unique contribution is the real-time cheating indicator technique, which estimates the probability of cheating while the exam is ongoing, facilitating early detection. Evaluated on a custom real video

dataset containing various cheating and non-cheating activities, the system achieved a remarkable prediction accuracy as high as **97.7%**. The authors emphasize that the combination of eye movement, head movement, mouth opening, and face recognition provides a robust set of features. They highlight the technique's cost-effectiveness, easy accessibility (no extra hardware or biometrics needed), and generalizability to variable-length videos. While the abstract does not detail specific limitations of their own system, the focus is on its significant advantages over existing methods, particularly its high accuracy and real-time capabilities.

Advances in Contextual Action Recognition: Automatic Cheating Detection Using Machine Learning Techniques
Researchers: Fairouz Hussein, Ayat Al-Ahmad, Subhieh El-Salhi, Esra'a Alshdaifat, and Mo'taz Al-Hami (2022) [8].
Work, Findings, and Discussions: This paper addresses the time-consuming and expensive nature of human proctoring, especially with the shift to electronic monitoring mechanisms. The authors highlight the inherent challenges in action recognition in videos, such as noise, viewpoint occlusion, scaling, illumination variations, cluttered backgrounds, camera motion, and brightness changes. To advance automatic cheating detection, they present a new framework for the learning and classification of cheating video sequences, specifically aiming for early detection of student cheating. A significant contribution of this work is the introduction of a new, publicly available dataset titled "actions of student cheating in paper-based exams." This dataset was meticulously designed and prepared to fill a gap in open-source resources, containing 37 video sequences covering five distinct cheating activities performed by 8 unique subjects in a classroom setting. From each frame, five well-known features were extracted: BRISK (Binary Robust Invariant Scalable Keypoints), MSER (Maximally Stable Extremal Regions), HOG (Histogram of Oriented Gradient), SURF (Speeded-Up Robust Features), and a combination of SURF&HOG. Frames were preprocessed by cropping to reduce dimensionality, and visual vocabulary codebooks were created using the bag of words technique and K-means clustering. A multiclass Support Vector Machine (SVM) classifier [23] was then used for frame-level classification. The framework's experimental results were described as "impressive and substantial." Notably, SURF features achieved the highest average accuracy of **91%** on the validation dataset. While "not cheating" and "exchange exam paper" classes showed consistently high accuracy, "using a cellular device" exhibited lower accuracy (75% to 92%), likely due to variations in phone appearance. The authors emphasize the challenging nature of their new dataset due to similar activities and human-object interaction. Future work suggests exploring more complex deep learning algorithms for feature learning, more appropriate features and classifiers, expanding the system to online exams with multiple subjects, and recording more dynamic environmental factors to enrich the dataset.

Detection of Malpractice in E-exams by Head Pose and Gaze Estimation
Researchers: Chirag S Indi, KCS Varun Pritham, Vasundhara Acharya, and Krishna Prakasha (2021) [9].
Work, Findings, and Discussions: This paper addresses the growing need for technological solutions to identify malpractice in e-exams, particularly focusing on detecting when a student's visual focus of attention (VFOA) deviates from the screen. The authors propose an end-to-end application designed to assist examiners in determining potential malpractice during online exams. The system operates by categorizing the student's VFOA data, which is derived from captured head pose estimates and eye gaze estimates using state-of-the-art machine learning (ML) techniques. The system's input requirements are

minimal, only needing a functioning internet connection and a webcam from the student. A key feature is that the examiner is alerted if the student's VFOA wavers from the screen more than a predefined threshold of times. If this threshold is crossed, the application saves the relevant data (when VFOA is off-screen) and sends it to the examiner for a manual review, allowing for a final judgment on whether it constitutes attempted malpractice or merely a momentary lapse in concentration. The system employs a robust hybrid classifier: one classifier is utilized when gaze values are successfully read, but if gaze reading fails (e.g., due to transmission quality issues or glare from spectacles), the model intelligently falls back to a default classifier that relies solely on head pose values to classify the attention metric. This hybrid approach significantly enhances the system's reliability in real-world scenarios. The model achieved an accuracy of **96.04%** in classifying the attention metric, demonstrating its effectiveness in identifying deviations in student attention. The discussion highlights the system's focus on a specific type of malpractice (deviation of visual focus) and its reliance on human intervention for the final decision, despite automating the initial detection and flagging. The hybrid approach is a notable strength, mitigating common issues that affect gaze detection.

Fraud Detection Based Online Test and Behavior Identification Implementing Visualization Techniques

Researchers: HarishBabu. Kalidasu, B.PrasannaKumar, and Haripriya.P (2012) [10].

Work, Findings, and Discussions: This paper addresses the inherent lack of guaranteed genuineness in online exam results, stemming from the distributed nature of proctors and examinees, the absence of robust authorization guarantees, and difficulties in trusting examination center heads. The authors argue that the increased distance in online communication significantly escalates the chances of malpractice and misbehavior, necessitating constant monitoring and the ability to stop exams based on learner behavior. To tackle this, they propose a "Fraud Detection based Online Test (FDOT)" and "Behavior Identification through Visualization Techniques (BIVT)" system. This system aims to be more effective than existing ones by continuously monitoring examinee behaviors and visualizing them for proctor interpretation. The paper discusses various authentication methods, including passwords, tokens (physical keys, cards), and biometrics (facial recognition, fingerprints, iris, voice, etc.), and different authentication system architectures (central, multi-factor, split, message). The core of their behavior identification lies in data visualization, describing techniques for 2D, 3D, and high-dimensional data, such as scatter plots, line graphs, icon-based methods (Chernoff faces, star glyphs), hierarchical techniques (dimensional stacking), and geometrical approaches (parallel coordinates). The main focus for cheating detection is on image processing. Images of students are recorded at regular intervals during the exam and compared with reference images of normal states. The method assumes a consistent exam environment (student behind a desk with only a computer, consistent desk/chair/clothes/environment, consistent webcam angle and light). A preliminary method, implemented in Matlab, calculates the difference between two images by subtracting pixels; if the distance exceeds a predefined threshold, it's flagged as a cheating state. The paper primarily proposes and discusses these methods rather than presenting concrete experimental results for its own FDOT/BIVT system. It highlights how data visualization can provide an effective overview of student behavior for proctors. A significant limitation is the reliance on strict environmental assumptions for the image processing method, which may limit real-world applicability. The authors also acknowledge that simple methods like typing speed changes for cheating detection can be prone to errors due to factors like exam stress. Future work suggests validating the proposed system using a face database, employing Discrete Cosine Transform (DCT) and Euclidean distance for comparison, and further developing

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visualization techniques for student behavior tracking.

A Systematic Review of Research on Cheating in Online Exams from 2010 to 2021

Researchers: Fakhroddin Noorbehbahani, Azadeh Mohammadi, and Mohammad Aminazadeh (2022) [11].

Work, Findings, and Discussions: This paper presents a comprehensive systematic mapping review of research on cheating in online exams published between January 2010 and February 2021. The authors identify a gap in the literature regarding comprehensive reviews specifically focusing on cheating motivations, types, detection, and prevention in online settings. Their methodology involved a systematic search across Google Scholar, Web of Science, and Scopus, using a carefully designed search query. From an initial 289 records, 58 publications were selected after rigorous filtering based on inclusion and exclusion criteria (e.g., English language, relevance to research questions, quality). A Credibility Score (CS) was assigned to each study by domain experts. Studies were categorized into four main topics: Cheating reasons, Cheating types, Cheating detection, and Cheating prevention, with further sub-classifications. Key findings from the review indicate that the greatest number of studies were published in 2017, with journal papers being the dominant publication type. Cheating prevention and detection emerged as the most prevalent research themes. The primary reason for cheating identified was that examinees perceive the rewards to outweigh the risks [21]. The review meticulously identified various cheating detection methods, including time delay and head pose analysis (Chuang et al., 2017 [22]), continuous authentication systems using biometrics (Aisyah et al., 2018 [23]; Bawarith et al., 2017 [26]; Traore et al., 2017 [27]), page focus/tab locking (Diedenhofen & Musch, 2017 [24]; Chua & Lumapas, 2019 [41]), and deep learning approaches for intelligent cheating detection (Tiong & Lee, 2021 [25]; Mengash, 2019 [44]; Hu et al., 2018 [48]). Statistical methods (Mott, 2010 [50]) and video summarization (Cote et al., 2016 [57]) were also noted. For cheating prevention, methods included honor codes, controlling mechanisms, warnings [21], strategies to minimize cheating opportunities [47], and the impact of video proctoring on test scores [31, 32, 52, 56]. The discussion highlights the review's comprehensive overview and its systematic methodology, ensuring robustness.

Conclusion

The rapid and widespread adoption of online education, significantly accelerated by global events, has undeniably underscored the critical need for robust and reliable online examination systems. While offering unparalleled accessibility and flexibility, this paradigm shift has simultaneously presented profound challenges in maintaining academic integrity and effectively detecting malpractice in remote assessment environments. Traditional human proctoring methods, though effective in physical settings, have proven labor-intensive, costly, and inherently limited in scalability for the vast scope of online examinations. In response, the academic and technological communities have increasingly turned to automated online proctoring systems, primarily leveraging advancements in Artificial Intelligence, particularly deep learning, as a promising solution.

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