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*Research Article*

# Predictive Analytics for Student Performance Based on Behavioural and Academic Data

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**Abstract:** The onset of the COVID-19 pandemic has hastened the shift from traditional classrooms to digital learning platforms. Online education rapidly became the primary method to prevent academic disruptions. Consequently, researchers have turned their attention toward understanding student engagement in virtual learning environments. This study proposes a novel approach to assess student behavior in e-learning systems. The system employs the Viola–Jones algorithm for initial detection based on motion tracking, followed by occlusion management through region-shrinking techniques. Human verification is performed using template matching, and key features are extracted at both the silhouette and skeletal levels. A genetic algorithm is then utilized for classification. This system aims to assist educators in recognizing disengaged or struggling students to provide tailored interventions. The model achieved accuracy rates of 90.5% and 85.7% on the MED and Edu-Net datasets, respectively, surpassing current standard methods.

**Keywords:** Crowd Management, Human Verification, Machine Learning, Big Data Analytics, GA Classifier; Viola–Jones.

## 1.Introduction

Over the past decade, the use of the Internet has expanded significantly, revolutionizing how people learn, shop, and conduct research [1-3]. The traditional classroom has evolved into a digitally supported environment. With the vast availability of online courses, certifications, and seminars, the conventional model of education has faced increasing scrutiny. This digital shift has compelled educational institutions to rethink and redesign their delivery methods to remain effective and relevant. Among the growing areas of interest are strategies for creating engaging online learning experiences and evaluating student satisfaction and behavior in these environments [4-6]. The necessity for such advancements became especially clear during the global COVID-19 crisis, which led to widespread school closures and pushed over 1.5 billion learners into remote education, according to UNESCO. In response, many institutions have rushed to implement digital tools that support virtual classroom engagement[7-8].

## 2.Related Works

The COVID-19 pandemic has accelerated the adoption of e-learning as an alternative to traditional classroom education [9-11]. As a result, educators and researchers are increasingly interested in understanding the behaviour of students in e-learning environments[12-15]. Behaviour analysis is a useful approach for studying student behaviour in e-learning, as it can provide insights into factors that influence learning outcomes and inform the design of effective interventions[16-17]. Behaviour analysis has been utilized in several types of research to look into how students behave in e-learning settings[18-19].

The behaviour of pupils during a computer-based training program, for instance, was examined by Kun et al using a microanalytic technique[20]. They discovered that students who exhibited more active learning behaviours, such as taking notes and asking questions, outperformed passive learners in terms of their learning results. Similarly, Liu et al. examined student behaviour in a massive open online course (MOOC) using data mining tools. They discovered that students were more likely to finish the course and receive higher scores if they participated in more discussion forums and course activities.

## 3.Proposed System Methodology

In this part, the suggested system methodology is explained. The entire workflow of the system is shown in Figure 1. The Motion Emotion Dataset (MED) and Edu-Net datasets have been chosen to assess the efficacy of the proposed technique in both indoor and outdoor settings, respectively. Six elements make up the system used to assess how well students behaved in an online learning environment. The complete algorithm has been presented in Algorithm 1.

Algorithm 1 Multistage processing to detect students' behaviour in e-Learning.

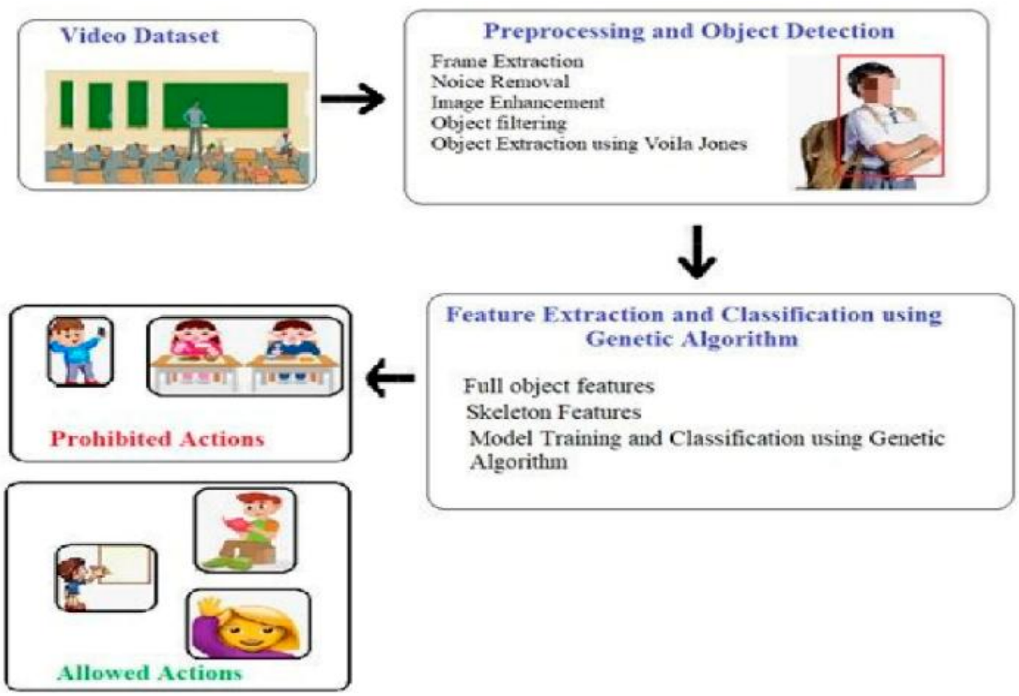


**Figure1:** Proposed methodology to detect learner behaviour.

To achieve accurate and successful outcomes, a strong and multifaceted technique was used in the development of our system for monitoring student behaviours in the classroom. Preprocessing was the first phase of this procedure, which was performed to isolate important classroom items and remove background noise. Objects outside of the established threshold range were eliminated, leaving just the characteristic human layout. Our dataset contains a variety of outdoor locations and objects that may have difficult shadows; thus, an additional step was included to improve the quality of the human silhouettes. In order to show human forms more accurately and clearly, shadows had to be found and then eliminated.

We employed the template matching technique to extract exclusively human data from the image data in order to improve the accuracy of our system. These steps came together to isolate and extract human silhouettes, which served as the basis for further analysis. Continuing with our methodology, the next critical phase involved the extraction of features from the human silhouettes utilizing conditional random fields. This step allowed for a more comprehensive understanding of the various aspects of human behaviour and posture within the classroom setting. To classify the activities performed by students as either allowed or prohibited, we employed a genetic algorithm. This sophisticated algorithm played a pivotal role in categorizing and analysing student behaviours, offering a dynamic and adaptive approach to the assessment of classroom activities. By integrating these various techniques and algorithms, our system was well equipped to accurately and efficiently track and categorize student behaviours, providing educators with valuable insights and tools for maintaining a conducive and productive learning environment.

### *3.1. Image Preprocessing*

Our dataset was in the form of videos. The next step we performed was frame extraction from the video, and then we utilized each frame to preprocess the image. As seen in Equation (1), a special median filter has been used to remove noise and smooth the video frame images that were retrieved. Then, the foreground objects' appearance was improved using image enhancement as shown in.

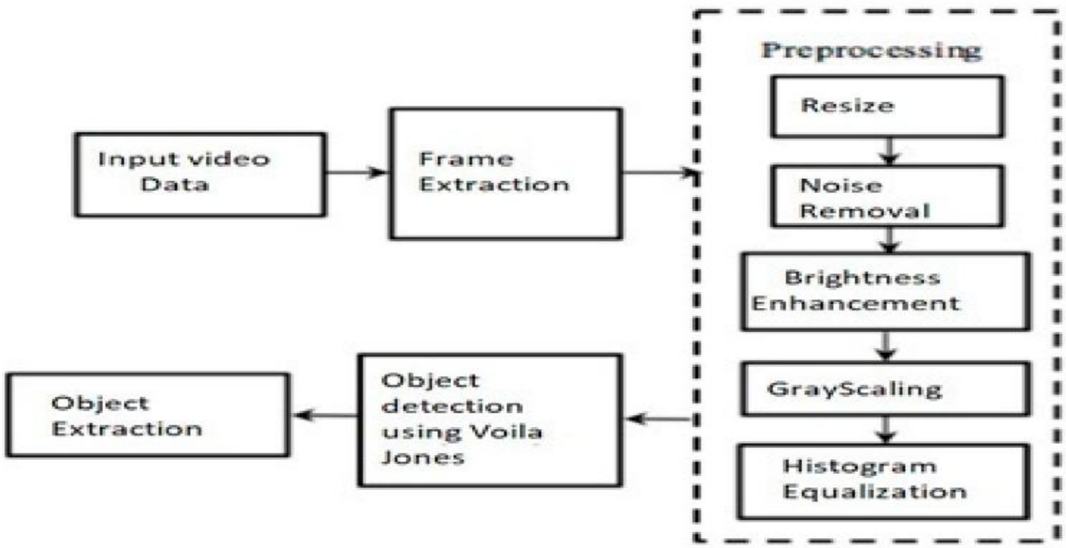


**Figure 2:** The process used to extract objects of interest in the image.

### *3.2. Object Extraction*

Object extraction was performed using the Viola–Jones algorithm which involves Haar-like features extraction, Ad boost training, and a cascade of classifier. The decision to use the Viola–Jones algorithm for human detection in the context of our research on monitoring student behaviours in the classroom was carefully examined and was influenced by a number of variables. We chose the Viola–Jones algorithm due to the specific benefits it offers within the scope of our project, despite the fact that deep learning-based algorithms have acquired significant popularity in recent years for their outstanding capabilities in object detection and categorization. The Viola–Jones technique is computationally effective and substantially faster than deep learning-based approaches. We were able to monitor and analyse student behaviours in a timely manner without adding a lot of latency due to its capacity to achieve real-time performance, even on hardware with constrained computational capabilities.

In comparison to deep learning-based techniques, the Viola–Jones algorithm also needs less training data. It can be difficult and time-consuming to gather a sizable dataset for deep learning models in a real-world classroom setting. The Viola–Jones method was a practical choice for our research because of its propensity to perform well with small datasets. Next step includes a set of rectangular Haar- like features defined to capture the difference between the object and background regions. Each feature was represented as the difference between the sum of pixel intensities in two rectangular regions. Using the Adaboost approach, a set of weak classifiers were trained on a set of positive and negative examples. Each weak classifier was trained to classify an image patch as containing the object or not based on a selected Haar-like feature, and then classifiers were combined into a cascade of strong classifiers. Each weak classifier in a strong classifier was trained to pass the positive data to the next stage while highly likely rejecting the background samples. The cascade of classifiers was applied to the input video frames by sliding a window over each frame and evaluating the objectless score for each window. The results are shown in Figure 3.

$$O(x,y)=\sum i\ \alpha i T\_i(f\_i(x,y)) \quad (1)$$


**Figure 3**: Object Extraction

### *3.3. Feature Extraction*

The feature extraction procedure for human silhouettes discovered by the layout verification module is described in this section. Full human silhouettes' features were extracted, as well as the skeleton against each silhouette. The features extraction outline is presented in Figure 4 and is divided into two directions.

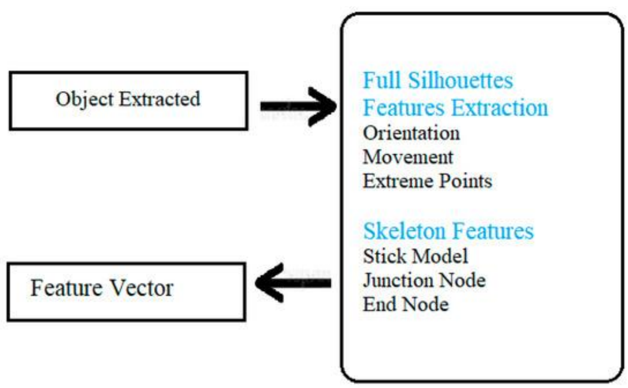


**Figure 4:** Features extraction for full body and skeleton levels.

#### *3.3.1. Full Silhouette Features*

The positions of each human silhouette in the current frame and the frame before it were obtained, as illustrated in Equation, and they were regarded as separate objects.

$$(Io,f)=Ix,y \in O P(Io,f)=Ix,y \in O \quad (2)$$

where the current frame is represented by f and the current silhouette by o. Movement of centroid among successive frames concerning time was used to determine the distance for each silhouette using Equation.

$$d=(x2-x1)2+(y2-y1)2 \tag{3}$$

$$velocity=dudt/\text{velocity=dudt} \tag{4}$$

Then, the velocity of each object was computed using Equation (6) and the distance was calculated using Equation; these factors were then used to distinguish between the allowed actions and prohibited actions.

$$\theta=tan-1(yx/) \tag{5}$$

$$\theta=\text{tan}-1(\text{yx}) \tag{6}$$

We first selected random points of the complete silhouette to describe the structure of the object, using Principal Component Analysis (PCA) to determine the orientation of the object. The coordinates or position of the object should be disclosed for each data point. The dataset's covariance matrix, which illustrates the connections between various dimensions of the data points, was then computed. The principle components were then obtained by applying PCA to the dataset. These elements were eigenvectors that showed where the data's greatest variance occurs. We may determine the object's fundamental orientation by examining the first principal component, which captures the most significant change. The orientation of the object can be inferred from the first principal component's direction (See Figure 5).

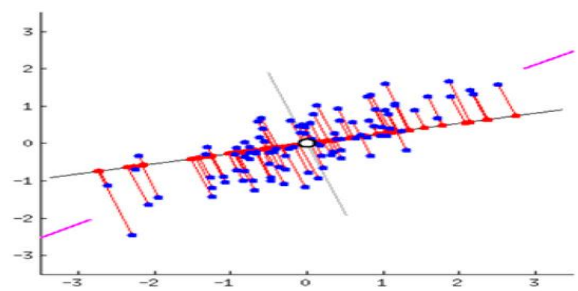

**Figure 5:** PCA to compute the orientation of the object.

### *3.3.2. Stick Model Features*

Stick models were used to extract the features at the micro level. The human silhouette's skeleton was first removed, and endpoints and junction nodes were located. Endpoints and junction points were utilized to draw the stick model in Figure 6 to demonstrate it. To connect the nodes, we employed the optical flow of each node presenting the model, as well as the distance and angle between the slants.

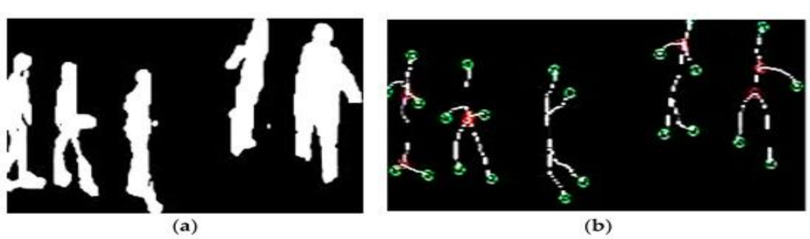


**Figure 6:** Stick model presentation of human silhouettes detected.
(a) Humans detected, and (b) Stick Model

### *3.4. Feature Optimization and Classification*

The genetic algorithm was utilized as a classifier, with each data point assigned to one of several predefined categories based on its features or attributes. To achieve this, the GA creates a set of candidate classifiers, each represented by a set of parameters that define its decision boundary. The fitness of each classifier is evaluated by its ability to correctly classify a set of training data, and the GA evolves the population of classifiers by selecting the fittest ones and generating new ones through crossover and mutation operations. The process continues until satisfactory classification accuracy is achieved on the training data, and the final classifier can then be used to classify new, unseen data.

The main reason for using the GA for classification is that it can search a large solution space and discover complex decision boundaries that may be difficult to find using other methods. However, the effectiveness of the GA depends on various factors such as the quality of the training data, the choice of genetic operators, and the number of parameters in the classifier. Nonetheless, the GA remains a popular and powerful technique for data classification in various domains such as image recognition and bioinformatics. The general architecture of the genetic algorithm is displayed in Figure 8. Initially, a population of the potential solution was created, where each individual represents a solution and is evaluated by the fitness function. The solution with a higher fitness value was chosen to become a parent for the next generation and parents were combined to generate a new population; mutation was performed to avoid premature convergence. The cycle repeated until a satisfactory fitness level was achieved. Once it was terminated, the individual with the highest fitness value was considered as the best solution.

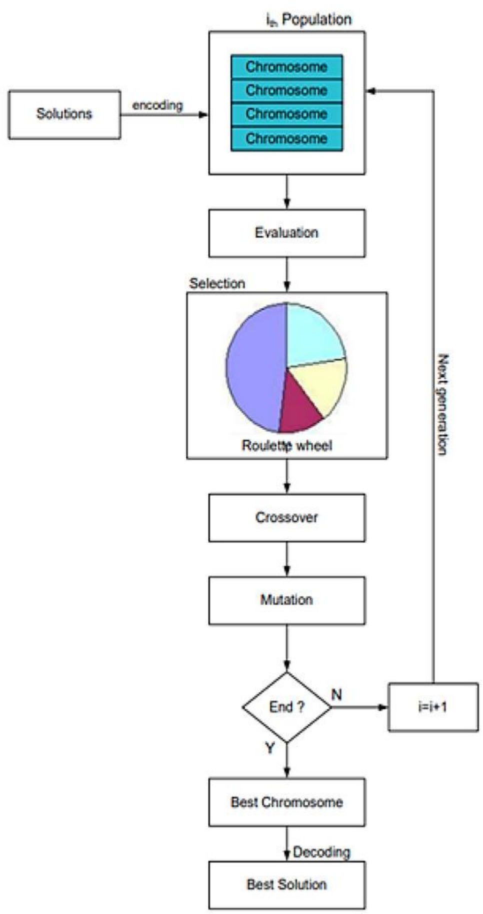


**Figure 7:** The architecture of the genetic algorithm with population distribution and selection.

## 4.Experiments and Results

This section discusses the dataset and the specifics of the research, such as the experimental setup, the performance of the suggested system, and a comparison analysis with cutting-edge techniques.

### *4.1. Dataset*

Two different datasets were used to evaluate the performance of the system in different environments and had different actions performed by multiple persons. The first dataset is made up of around 44,000 normal and abnormal video clips divided across 31 video sequences.

#### *4.1.1. MED (Motion Emotion Dataset)*

Two significant segments in various indoor-outdoor situations can be found in the MED dataset. One section includes video clips that demonstrate five distinct behaviours: panic, fighting, congested area, obstacle or strange object, and neutral. The other section, on the other hand, is made up of various video sequences that provide information on six distinct emotions: anger, happiness, excitement, fear, sadness, and neutrality.

Figure 8 displays a few instances of MED sceneries. We have combined these emotions in two classes and categorized all emotions and behavioural videos into allowed and prohibited behaviour categories.

**Figure 8:** Examples of different scenes of the MED dataset.

The statistical analysis discussed in the preceding sections offers important insights into how well the suggested system performs in identifying and categorizing both permitted and forbidden behaviors in the MED and Edu-Net datasets. The performance metric of precision shows how well the system performs in correctly identifying actions while reducing false detections. A great overall performance is indicated by the average accuracy values for both datasets, which vary from 85.75% to 90.5%.

#### *4.1.2. Edu Net Dataset*

There are several videos of various e-learning-related acts on EduNet [52]. The dataset, which includes several teachers and pupils, was obtained from a classroom setting. Videos show a variety of permitted classroom behaviours, such as standing, writing on the board, raising hands, and maintaining a book in hand. Prohibited behaviours include eating, using a phone, and bouncing around during class. Figure 9 shows some examples of the EduNet dataset having multiple allowed and not allowed action.

**Figure 9:** the EduNet dataset having multiple allowed and not allowed action.

### *4.2. Performance Metric and Experimental Outcome*

Precision [was chosen as the performance metric for our system evaluation to assess its effectiveness. Equation (8) was used to calculate precision , Precision=tc(tc+fc )/, where tc represents the total number of prohibited actions classified correctly and fc represents the total number of false detected actions. The results of the MED and Edu-Net datasets are shown in Table 2. Classes are categorized into allowed and prohibited behavior and each subcategory has been evaluated.

## 5.Discussion

Access to educational opportunities has been made simpler due to the growth of e-learning. However, concerns about student misconduct and reduced engagement have also arisen as a result of the increased use of e-learning platforms. A mechanism has been developed in place to solve this problem that looks at visual data to find students practicing unauthorized behaviours during online learning. This article offers a comprehensive overview of the system, its elements, and its functionality.

The preprocessing stage of the system, which aims to lower noise and improve image quality, is the first stage. The Viola–Jones technique is then used for object detection to determine whether a person is present in the frame. By using template matching, it is possible to confirm that the identified object is a human. Each silhouette is subjected to skeleton extraction, and feature extraction is conducted for both skeleton points and human silhouettes. A genetic algorithm is then used for classification.

The system was assessed using a collection of videos of students engaging in online learning activities. The algorithm accurately identified 90.5% of the prohibited actions, including talking, using a phone, standing on a chair, and sleeping. The system's performance was also assessed in terms of detection time, and it was found that it ran in real time with a frame rate of 30 frames per second.

An important area of interest in the realm of education is the assessment of student behaviours in e-learning. Understanding and observing student behaviour has become essential for teachers and educational institutions to effectively help students and improve learning outcomes as a result of the rising popularity of online learning platforms.

The objective of this discussion is to critically examine student behaviour assessment in online learning and its implications for educational practices.

## 6.Conclusions

E-learning is the top trending source of education in this era especially after the COVID-19 pandemic. Educators and researchers are paying more attention to improving e-learning systems. The behaviour of students and their engagement level is the most important factor of the e-learning system. This system was implemented to identify the behaviour of students in an e-learning environment. Multiple datasets were used to evaluate the performance of this system. Videos were converted into frames and then objects were segmented to narrow down the region of interest. Features for each object and its skeleton models were used to characterize the behaviour of students. Datasets were divided into allowed and prohibited behaviours. Experiments were performed and an average accuracy of 89% and 85.5% was achieved on both datasets.

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