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STUDENTS SIZE DETECTION COUNTING SYSTEM ON CAMPUSES USING ARTIFICIAL INTELLIGENCE: DEEP LEARNING

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ABSTRACT :

Student size counting is essential for various real-world applications, including resource management, traffic control, security, lecture hall distribution, and campus disaster management. Traditional methods like manual counting, register-based records, and sensor-based systems are time-consuming, tedious, and prone to errors due to dynamic movements. This has led to the adoption of crowd-counting methods using CCTV video feeds, which effectively capture the dynamism of crowd movements. Accurate crowd counting is crucial for emergency situations like fire outbreaks or earthquakes, enabling authorities to make informed decisions about resource allocation. Recent advancements in crowd-counting techniques include detection-based, density-based, and regression-based methods. However, these methods often lack accuracy, especially in highly congested scenarios. Deep learning has emerged as a promising solution for crowd-counting challenges, particularly in complex environments like lecture halls, sports events, and religious gatherings. Single-image crowd counting methods, though effective, face challenges due to obstructions and complex backgrounds. Recent work has explored multi-object tracking systems to improve accuracy, such as incorporating distance calculations between bounding boxes. This study proposes a Multi-Centroid-Based Multi-Object Tracking Algorithm to address the limitations of existing systems, particularly the lack of precision in distance calculations. The proposed system leverages Convolutional Neural Networks (CNNs) and OpenCV for real-time student size detection, offering improved accuracy and performance. The study evaluates the proposed system using performance metrics like Mean Absolute Error (MAE) and Mean Squared Error (MSE), comparing it with existing CNN-based algorithms. The results demonstrate that the proposed system outperforms traditional methods, making it suitable for applications in public safety, traffic control, and event management. This project highlights the potential of deep learning in addressing crowd-counting challenges and recommends its adoption for real-time monitoring and analysis in various institutional and governmental settings.

Keywords: Crowd Counting, Student Size Detection, Deep Learning, Convolutional Neural Networks (CNN), Multi-Object Tracking and Centroid-Based Tracking Algorithm

1. Introduction :

Student size counting is essential to serve many real-world applications, such as resource management (such as water, food supply), traffic control, security, distribution of students in lecture halls, campus disaster management etc (Zhang, et a, 2016). The traditional methods for crowd-counting such as manual counting, using registers to maintain records of each person, and counting through use of sensors are time consuming and tedious, and may produce fallible results due to dynamic movements. This has led to the evolution of crowd-counting methods which rely on CCTV video feeds. The major benefit of using counting methods on video feed is that the dynamism of people's movement cannot be incorporated in any of the previous ways of crowd counting. This requires a modern outlook into the problem. An accurate crowd counting system provides solutions for emergency situations such as fire outbreaks, earthquakes and many other disaster situations. In these conditions, an estimate of the crowd would allow the concerned authorities to make the correct decisions regarding supplies of resources (Simonyan, K. & Andrew, Z. 2014). Recent solutions to the problem of an accurate estimate of crowd count have brought up techniques such as crowd counting using detection, density and regression (Boominathan, L. Srinivas S.S, & R. Venkatesh, B. 2016).

It is necessary to understand the risk analysis and safety aspect of students' dynamics at various important places on the campus which are related to sports, cultural day, religious (campus chapels and mosque), lecture halls and the campus environment. The complexity of monitoring, tracking and counting increases with the size of the students.

Many networks have been proposed to deliver a solution for crowd monitoring during a highly congested scene like the ones mentioned above. In recent years, interest in the visual analysis of crowd scenes has grown due to widespread deployment of security cameras for crowd surveillance, traffic, and planning management and even counting cells. Deep learning is a promising methodology that is used in solving such detection problems. Single image crowd counting method evaluates the number of people in the crowded image. Conventional methods are challenging due to severe obstruction and complex backgrounds. Crowd (students) count detection has various applications such as public safety, scheduling trains, traffic control etc. Most of the related work done in this field included crowd (students) detection using detection and regression methods, RGBD counting and multitask strategies. These methods lacked accuracy. On that it is possible to incorporate a model that calculates the distance between the bounding boxes and thus improves the precision of the violation as the system developed by (Subashree, et al., 2021). Hence, there is a need to develop a multi-object tracking system for crowd (students) detection system with high accuracy.

2. Literature Review :

Crowd counting is treated as an object/person detection problem in detection-based techniques, which assumes that a crowd is made up of individual items (Liu, W. Salzmann, M. & Fua, P. 2019). Handcrafted features were used in early works to detect people, but they were not resistant to extreme large-scale variance or occlusion in crowded scenes or clustered settings (Shen, et al., 2018). Despite the success of deep network-based object detectors in recent years, impressive object detection results, they still outperform regression-based methods when it comes to crowd counting (Ge, W. & Collins, R. T. 2009). A video-based face recognition which works on human face detection. The work done here works efficiently on challenging scenarios like multiple shot videos and surveillance videos with low quality frames.

However, it does not work with people wearing masks. Several studies have looked into RGBD crowd counting in order to better estimate crowd counts. The majority of these studies concentrate on using depth information to increase crowd scene person/head detection. (Li et al., 2008). Their detection module, on the other hand, does not outperform the module for regression. Meanwhile, since the depth map is not explicitly fed into the regression module, it is underutilized (Wang, Lu, & Nelson HC Y. 2009) which performs crowd count classification and density map estimation together, but the accuracy in detecting faces is low.

3. METHODOLOGY :

Deep learning is often regarded as a branch of artificial intelligence. It's an area that relies on analyzing computer formulas to learn and improve. Although AI makes use of simpler assumptions, Deep learning makes use of phoney neural networks that are meant to simulate how people consider and understand. Up until now, neural organizations were constrained by figuring power, and thus intricacy was restricted. Larger, more refined neural networks have been made possible by advances in Big Data processing, allowing computers to notice, understand, and respond to complex situations faster than humans. Image order, language interpretation, and discourse acknowledgment have all been aided by deep learning.

3.1 ANALYSIS OF THE EXISTING SYSTEM

This part of the research described the analysis of the existing system by (Subashree, D. et al., 2021). In figure 1 the architecture of the existing system is given.

Video streaming

For object detection, the researchers worked with a webcam and calculate the Frames Per Second (FPS) throughput rate. When working on this problem the first two constraints to think of is capability with FPS and Accuracy.

Pre-Processing

Frames are pre-processed by resizing and switching to rgb. OpenCV is a library for performing common computer vision and image processing tasks. Deep neural network inference, opening and writing video files, and showing output frames to our screen will all be done with OpenCV.

Object Detection

It is a computer technology that deals with identifying instances of semantic objects of a certain class in images and videos and constructing bounding boxes around those objects. It is related to computer vision and image processing.

Object Tracking

The centroid tracking algorithm for this. The center is calculated using bounding boxes. The distance between new and existing centroids is then determined using Euclidean geometry. It also unregisters objects that have been removed from the field.

Algorithm

Centroid-based Tracking Algorithm

Centroid-based tracking is a tracking algorithm that is simple to understand but extremely effective. Since it is based on the Euclidean distance between one current object centroids and the second new object centroids between subsequent frames in a film, this object tracking algorithm is known as centroid tracking. The centroid tracking algorithm uses (x, y) coordinates for every detected object in each frame, assuming that some sets of the bounding box are transferred. Bounding boxes must be calculated for each frame of the film, or, to put it another way, for each object identified by the camcorder. Following the assignment of

bounding boxes within the frame with their (x, y) coordinates, the centroid of each bounding box is determined, and each bounding box is given a unique

ID. The centroid of an object is computed in each subsequent frame using the bounding box definition that we discussed earlier. However, giving a new unique ID for each detection of the thing which hinders the objective of object tracking, so we'll see if we can compare the centroid of the new object to that of an existing object to resolve this, and to do so, we'll use the distance formula to measure the Euclidean distance between the two objects.

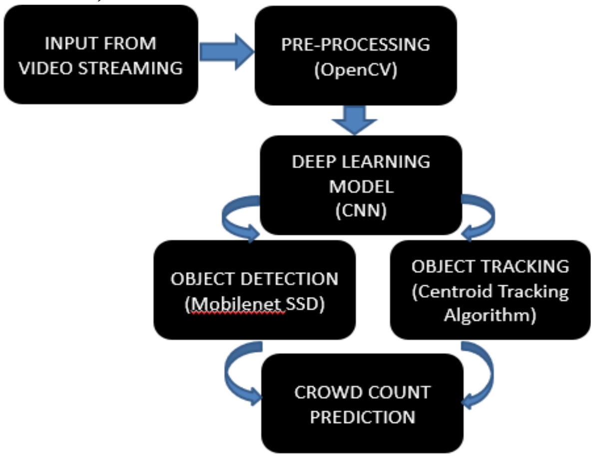

Figure 1: Architecture of the Existing System (Subashree, D. et al., 2021)

3.2 Weakness of the Existing System

Using the Centroid based tracking algorithm lacked accuracy. The algorithm cannot calculate the distance between the bounding boxes and thus improves the precision of the violation.

3.3 Proposed System

The proposed system will follow a similar methodology as that of the existing system but the algorithm will change following its weaknesses.
The proposed system will make use of Multiple Centroid-Based Multi-Object Tracking algorithm. It is a technology used to object identification, object location information extraction and analysis, object motion tracking from the image signal in real time. It has a very wide range of application in military industrial, security, and other fields; the development prospects are bright. The proposed method will solve the problem of the existing system. Figure 2 below describes the architecture of the proposed system; the proposed system will follow same methodology as in the existing system but with a slight difference, the proposed system will use a Multi Centroid based Multi Object Tracking not the Single Centroid tracking system as proposed in the existing system.

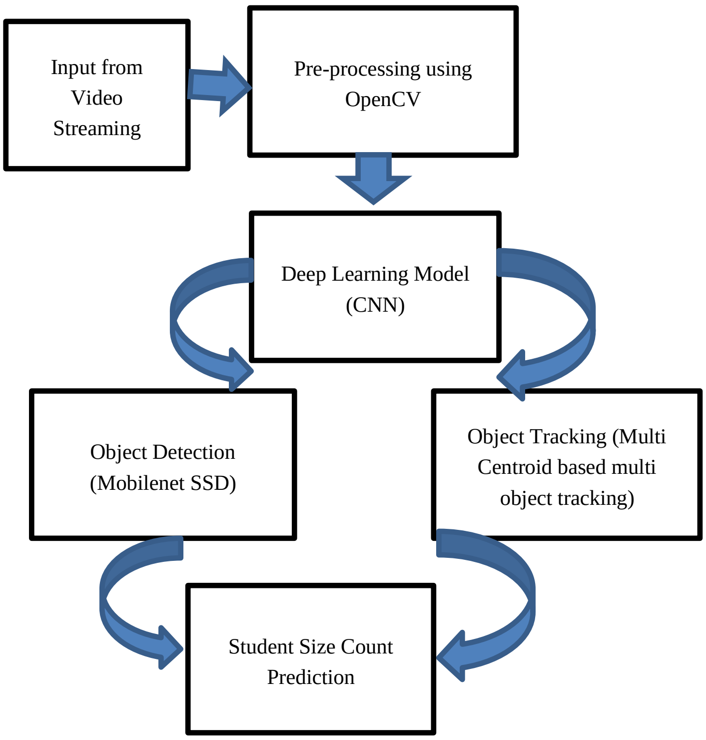

Figure 2: Architecture of the Proposed System

Implementation or Simulation Environment

OpenCV (Open-Source Computer Vision Library) is a python programming library for computer vision and artificial intelligence. The aim of OpenCV was to give PC vision applications a logical framework and to speed up the use of machine learning in business processes. The library contains 2500 enhanced figures and includes a detailed game plan for masterpieces as well as cutting-edge PC vision and AI computations.

Results and Discussion

In this section, we described the analysis of the learned representations in Crowd Counting using centroid tracking algorithm. The simulation was carried out in Python 3.11 and OpenCv which has different libraries.

Dataset

This dataset is downloaded from kaggle an open source and consists of images of people, the following attributes. The dataset was divided into different id with the number of people in an id.

Table 4.1: Distribution of Dataset with ID and number of people

	id	People
0	1	35
1	2	41
2	3	41
3	4	44
4	5	41

Loading of the Dataset

The images contained in the dataset were loaded in vector format.

Centroid-based Tracking algorithm

Centroid-based tracking is a tracking algorithm that is simple to understand but extremely effective. Since it is based on the Euclidean distance between one current object centroids and the second new object centroids between subsequent frames in a film, this object tracking algorithm is known as centroid tracking. The centroid tracking algorithm uses (x, y) coordinates for every detected object in each frame, assuming that some sets of the bounding box are transferred. Bounding boxes must be calculated for each frame of the film, or, to put it another way, for each object identified by the camcorder.

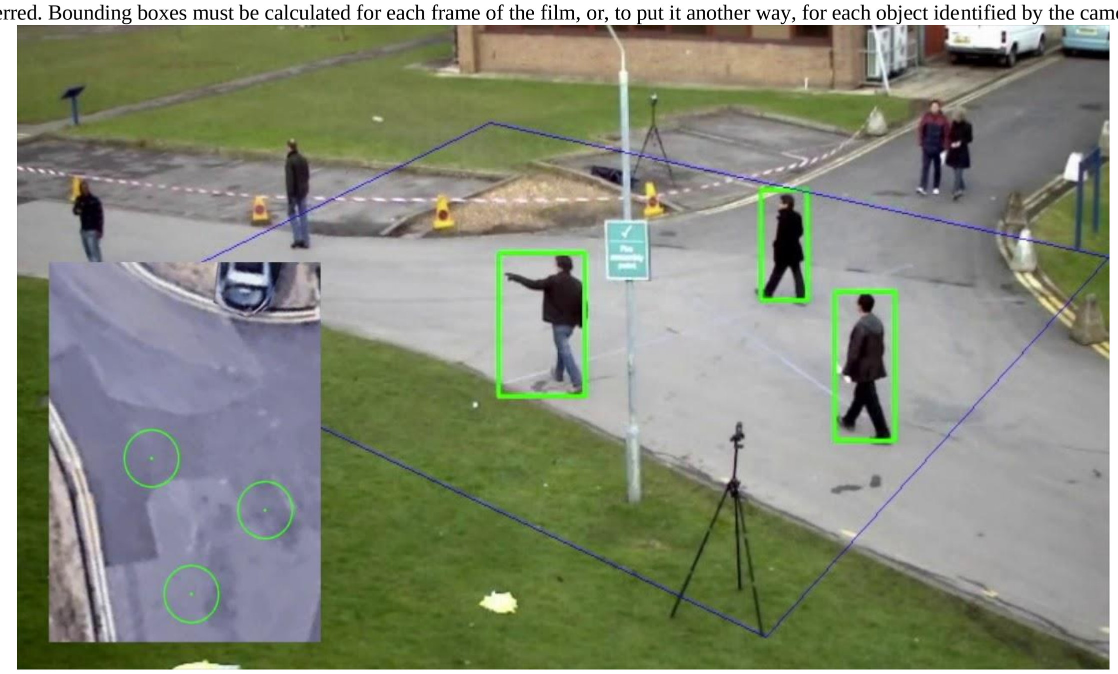

Figure 4.1: Live video footage showing boundary boxes

Structure of the Convolutional Neural Network

The figure below is the structure of the CNN algorithm used for crowd counting with: GTD as Ground Truth Density, ED as Estimated Density, FM as Feature Map, L as Loss (Error), W as Weight. The input (image) is labelled then the computation of the ground truth density is calculated then an object is counted. One loss function was introduced to optimize the model also the relative count loss helps to reduce the variance of the prediction errors and improve the network generalization on very sparse crowd scenes.

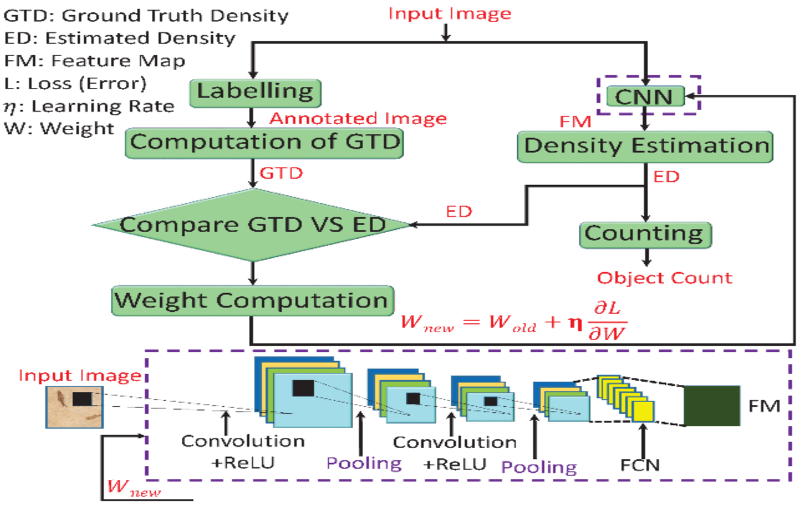

Figure 4.2: The Structure of CNN used

4. Performance Evaluation :

In other to measure the performance of the model, there is different performance evaluation metrics used.

Mean Absolute Error: is one of the many metrics for summarizing and assessing the quality of a machine learning model. So it's simple the subtraction of predicted values from the actual values. The prediction error is taken for each record after which we convert all error to positive. In the figure below, the mean absolute error is plotted against the epochs. Epoch is the number of passes during the training of a model, the figure shows a model being trained, as the epochs go by, the algorithm learns and so does its errors on the validation set. This indicates that the model has started to overfit the training data.

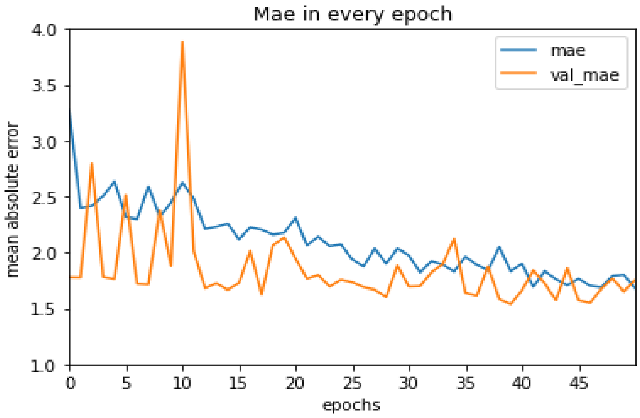

Table 4.1: performance of various CNN algorithms

Algorithm	Structure	MAE	MSE
M-CNN	22	15.7	29.3
CNN	22	11.5	17.2
Cascade CNN	22	14.9	28.6
CSRN	22	19.8	32.7

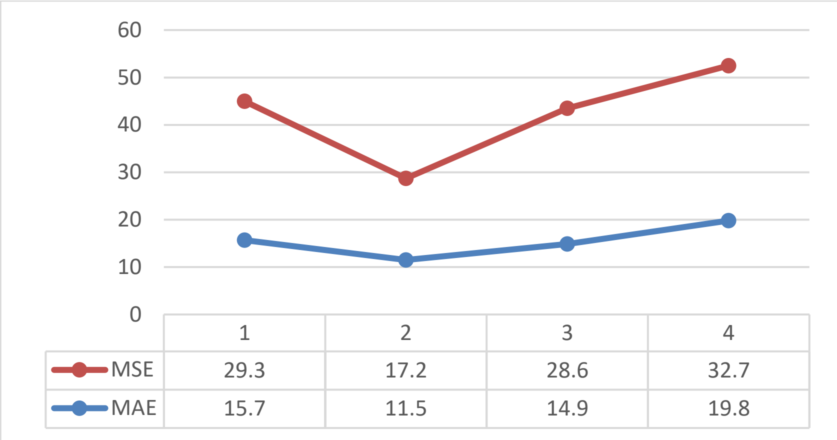

Figure 4.3: Graph of Various CNN performance for MAE and MSE

5. CONCLUSION :

The major aim of this project is developing real time Student size detection. The student size detection system was developed using python programming software, Convolutional Neural Network was used and also the performance of the proposed system was compared with various CNN algorithms, the proposed CNN algorithms out performed more than the other CNN algorithms.

This study has addressed some pertinent issues which our various systems of government and individuals; these issues include;

i. The detection of a criminal lost in a crowd
ii. Abnormal event detection
iii. Congestion analysis
iv. Gender classification
v. Detection of elderly people
vi. Knowing the number of people in an event or a location, etc

This project is recommended to both government and non-governmental institutions for its effectiveness. Apart from institutions, government agencies can used it to for instance in a market to improve its analysis whether to increase the size of the market or not. Businesses like shopping mall can use it to determine the number of people entered or exited the mall at a given time. The applications of this project are too numerous to mention.

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