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Lightweight Deep Learning Model for Weapon Detection

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Abstract- Public safety in public areas has become a significant concern for governments and businesses globally. Video surveillance systems are being increasingly integrated to ensure public safety, with deep learning techniques enhancing their ability to detect potential threats. Traditional video surveillance often relies on passive monitoring, but with advancements in AI, surveillance systems can now actively detect risks such as weapons (guns and knives) in real- time. This paper presents a deep learning-based system for weapon detection using MobileNet- V2, a CNN model known for its computational efficiency. MobileNet-V2 has shown an improvement of approximately 35% in processing speed compared to its predecessor, MobileNet-V1, while maintaining similar accuracy levels. This increase in speed is crucial for real-time weapon detection, where quick identification and response are vital to preventing threats. The study compares two approaches to weapon detection using CNNs, evaluating MobileNet-V1 and MobileNet-V2. The results indicate that MobileNet-V2 outperforms MobileNet-V1 not only in terms of speed but also in its ability to maintain high accuracy, marking a significant advancement in the field of weapon detection through deep learning. These improvements are vital in practical applications, such as public spaces, where large amounts of video data must be processed rapidly. The proposed system demonstrates a clear enhancement over prior methods in detecting guns and knives, offering a reliable, fast solution for real-time surveillance. This research highlights the effectiveness of MobileNet-V2 in improving public safety through advanced AI technology, providing a scalable solution for detecting threats in urban environments.

Keywords- Smart Cities, Industrial Informatics, Social Media Analytics, Citizen Emotions, Emotion Detection, Sentiment Analysis, Natural Language Processing (NLP).

I. INTRODUCTION

The presence and use of weapons in public places represent a major challenge to modern society, particularly in countries where weapon purchase is legal or poorly controlled. Crowded environments are especially vulnerable to mass shootings, which have become one of the most dramatic problems faced today. Traditional video surveillance systems, such as closed-circuit television (CCTV), are useful for remote alarm verification and intruder detection but typically require constant human supervision. Research indicates that the concentration of a security guard monitoring a camera panel decreases catastrophically after just 20 minutes. By applying artificial vision algorithms and machine learning techniques to video surveillance feeds, security can be significantly enhanced. Deep learning, in particular, offers the potential for automatic monitoring of larger spaces with fewer devices, reducing the heavy reliance on human factors for threat detection..

II. LITERATURE REVIEW

Harsh Jain, Aditya Vikram, Mohana, Ankit Kashyap, and Ayush Jain (2020) proposed a weapon detection system using Artificial Intelligence and Deep Learning for security applications. Their work focused on automatic gun and weapon detection using Convolutional Neural Networks (CNN), SSD, and Faster R-CNN algorithms. Two different datasets were used, including pre-labeled and manually labeled images. The study concluded that both algorithms produced good accuracy, but there exists a trade-off between detection speed and accuracy in real-time applications. ◆

Akcay, Kundegorski, Willcocks, and Breckon (2018) studied the use of deep convolutional neural network architectures for object classification and detection in X-ray baggage security imagery. Their research utilized transfer learning to improve detection accuracy when limited training data was available. Various CNN-based approaches such as SW-CNN, Faster R-

CNN, R-FCN, and YOLOv2 were compared. The results showed that YOLOv2 and Faster R-CNN achieved superior object detection performance with high mean average precision (mAP). ◆

Alina Kuznetsova and colleagues (2018) introduced the Open Images Dataset V4, which provides large-scale annotated datasets for image classification, object detection, and visual relationship detection. The dataset contains millions of images and bounding box annotations for object detection tasks. This dataset plays an important role in training deep learning models for weapon detection because it improves the model's ability to identify objects accurately in complex scenes. ◆

Olmos, Tabik, and Herrera (2017) proposed an automatic handgun detection alarm system in videos using deep learning techniques. Their approach focused on minimizing false positives while detecting weapons in surveillance videos. The researchers evaluated both sliding window and region proposal approaches and found that Faster R-CNN-based models provided highly accurate results. The system successfully generated alarms within a very short time, making it suitable for real-time surveillance systems. ◆

III. METHODOLOGY

The existing weapon detection system primarily relies on manual surveillance and traditional image processing or machine learning techniques for identifying weapons in images and video streams. Security personnel continuously monitor CCTV footage to detect suspicious objects, which is time-consuming and prone to human error due to fatigue and lack of attention. Conventional methods use handcrafted features such as shape, edge, texture, and color information combined with machine learning algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, and Random Forest for classification. Some systems also employ deep learning models such as Faster R-CNN and SSD, which provide better detection accuracy but require high computational power, large memory, and expensive hardware resources.

These existing approaches often struggle with real-time performance, varying lighting conditions, object occlusions, and complex backgrounds, resulting in delayed detection and higher false alarm rates. Therefore, there is a need for a lightweight deep learning-based weapon detection system that can provide accurate, fast, and real-time detection while using fewer computational resources.

Disadvantages of existing system:

- Manual Monitoring Requirement
- Delayed Threat Detection
- Low detection Accuracy
- Poor Performance in Real Time Application

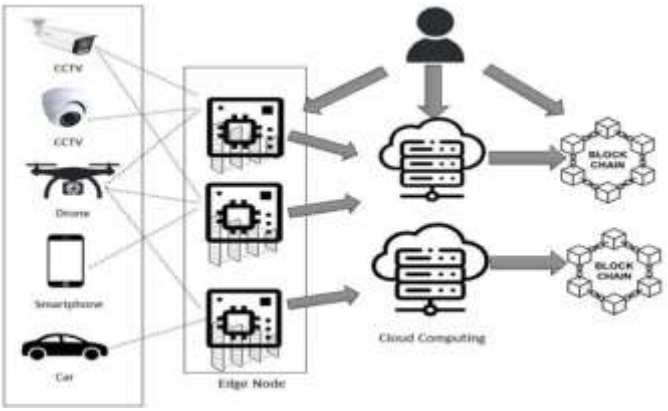
PROPOSED SYSTEM

Video surveillance is commonly used for: Remote video monitoring: to protect against theft, burglaries, and dishonest employees. Facility protection: to protect the perimeter of the property or the perimeter of buildings. Monitor operations: to monitor day- to-day operations and as a tool to streamline operations but daily monitoring the daily suspicious with manual is somewhat difficult so we have solve problem of live surveillance with automatic alert system using MobileNet-v2 technique.

Advantages Proposed System Advantages

- High Accuracy
- Efficiency and Speed
- Scalability
- Contexual understanding

SYSTEM ARCHITECTURE



The system architecture for the lightweight deep learning–based weapon detection system is designed as a streamlined pipeline that efficiently processes visual data from input sources such as CCTV cameras, webcams, or video files to detect weapons in real time. Initially, the input layer captures continuous video frames, which are then passed to a

preprocessing module where resizing, normalization, and noise reduction are performed to make the data suitable for model inference.

MODULES:

1. Sound Device:

Sound device, as stated in its documentation, python-sound device "provides bindings for the Port Audio library and a few convenience functions to play and record NumPy arrays containing audio signals". In order to play WAV files, sound file need to be installed, to open WAV files as NumPy arrays.

2. Sound File

Functionality: This module is responsible for both reading and writing sound files. Underlying Technology: It utilizes lib and file, which is a free, cross-platform, open-source library. Compatibility: It supports many different sampled sound file formats and runs on multiple platforms, including Windows, OS X, and Unix.

3. Clear Output

Context: This is a component of the Python toolkit, which is designed to enhance interactive Python use. Primary Use: The clear output method is specifically used to clear the output of a cell within interactive frontends like notebooks

4. TensorFlow

Core Definition: TensorFlow is an open-source artificial intelligence library that uses data flow graphs to build models. Neural Networks: It is designed to allow developers to create large-scale neural networks consisting of many layers.
Applications: The library is primarily utilized for tasks involving classification, perception, understanding, discovery, prediction, and creation.

5. CV2 (OpenCV)

Definition: Known as Open Source Computer Vision, this is a popular library aimed at real-time computer vision.
Language & Interface: While it is written in C++ and maintains its primary interface in C++, it is widely used with Python for computer vision tasks

IV. IMPLEMENTATION

The proposed project is implemented as a real-time weapon detection system using Deep Learning and Computer Vision techniques. The system automatically detects weapons such as guns and knives from surveillance video streams and generates alerts whenever a weapon is identified. The implementation is based on the MobileNet-V2 architecture, which provides high detection accuracy with low computational complexity, making it suitable for real-time applications. The system consists of modules such as video acquisition, image preprocessing, feature extraction, weapon detection, and alert generation. Video frames are captured using surveillance cameras and processed through the trained MobileNet-V2 model. The model identifies weapons, draws bounding boxes around detected objects, and triggers alerts for security personnel. TensorFlow, OpenCV, NumPy, Sound Device, and Sound File libraries are used to implement the system efficie.tly.

V. EXPERIMENTAL RESULTS

HOME PAGE

Fig: Home Page

This image show the home page for the analysis of the weapon detetion for weapon likes Gun and Knife .

LOGIN PAGE

Fig: LOGIN INTERFACE

This interface show the login page for the admin for weapon detection where administrator enter the User ID and password to access the System securely

INPUT PAGE

Fig : INPUT PAGE

This interface displays the project interface where we upload the files or we can use live camera for weapon detection. This interface used by the client for detection for the weapon.

RESULT

Fig: WEAPON DETECTION

The interface displays the weapon detection results for uploaded videos. It shows the detected weapon and highlights the detected weapon by rectangle box with red line around it and give the voice over for when the weapon detection is successful

VI. CONCLUSION

In this paper discusses Public and crowded areas are still the target of many violent acts. Video surveillance can be helped by automatic image analysis using artificial vision. This paper describes the implementation of several weapon detectors for video surveillance based on MobileNet-V2 methodologies. For training, gun and knife images from the work of Olmos et al. and COCO dataset have been used. Several transformations such as rotations, scaling or brightness were applied in order to augment the datasets. Detectors were developed using the Two approaches have been compared taking as CNN the new model is about 35% faster with the same accuracy than MobileNetV1. Both detector results improve upon previous literature studies evidencing the effectiveness of our detectors.

VII. FUTURE ENHANCEMENMTS

The any-time video surveillance using mobilenet-v2 can be implemented with RCNN for further increase of finding predictions and to increase the percentage of custom objection detection.

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