SURVEY PAPER ON DETECTION OF WEAPON USING CNN AND YOLO

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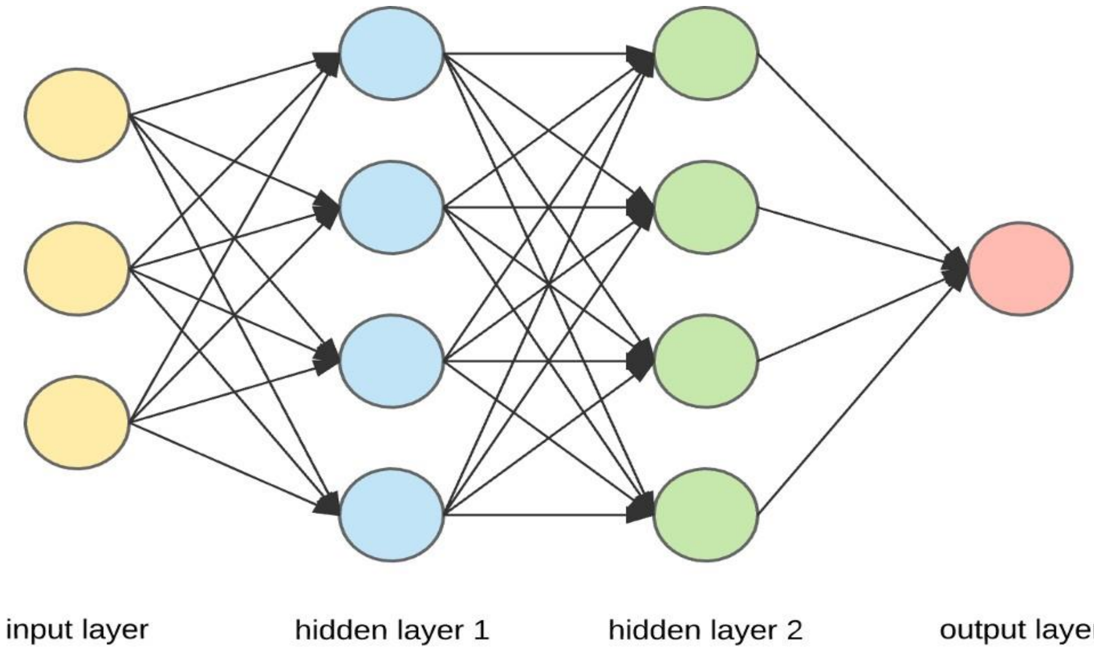
ABSTRACT

The world is becoming more unsafe day by day. The crime rate continues to rise with shootings, robberies and massacres in public areas. Due to increasing unrest everywhere, there is a great demand for safety and security. Systems such as security cameras that are equipped with real-time weapon detection technology are being implemented to help protect the safety of citizens. However, current weapons detection technologies have limitations: they are limited to detecting guns and/or knives. Criminals, on the other hand, are not limited to guns and knives. Therefore, this research is to construct an optimal neural network architecture to identify 6 commonly used weapons captured from a dataset of images. The research was conducted to develop a technology that would help arrest criminals before they commit crimes to protect the safety and security of citizens. The process starts with building an optimal Convolutional Neural Network (CNN) and an optimal transfer learning model. The validation accuracies of these models are evaluated and compared to each other. The final neural network model achieved 99.31% training accuracy and 95.55% validation accuracy, thus correctly classifying different weapon images.

INTRODUCTION

Computer vision is used everywhere today. It is used for many different functions, from detecting diseases to predicting criminal activity in an area. Notably, criminal justice is an area that requires AI's assistance. Since security cameras are installed in most public spaces, they can be used to detect criminalsand criminal activity through images. Imagine a system where security cameras are equipped with technology that allows for detecting weapons in real time.

A Convolutional Neural Network (CNN) is one of the most common methods used for an image classification task. In a CNN, the model starts to understand data by learning its patterns. A CNN is, fundamentally, a neuron network that takes in one or more tensor(s) as input and outputs one or more tensor(s). A tensor is a container of data. Neural networks are composed of many layers that are connected to each other by artificial neurons. The number of layers of a CNN is not a static



variable, however. The number of layers can vary based on the amount of input and/or accuracy of the model.

Levels of gun-related violence vary greatly among geographical locations and countries. The global death toll from

use of guns may be as high as 1,000 dead each day. Nowadays, with the accessibility of huge datasets, quicker GPUs, advanced machine learning algorithms, and better calculations, we can now effectively prepare PCs and develop automated computer-based system to distinguish and identify numerous items on a site with high accuracy. Recent developments indicate that machine learning [3–6] and advance image processing algorithms have played dominant role in smart surveillances and security systems [7, 8].

LITERATURE SURVEY

Reducing the life-threatening acts and providing high security are challenging at every place. Therefore, a number of

researchers have contributed to monitoring various activities and behaviors using object detection. The idea for real-time weapon detection using computer vision first came out in 2007 when scientists proposed a real-time firearm detector by utilizing a CCTV camera feed [8].

Weapon detection algorithms are frequently used to screen monitoring and CCTV footage. To identify footage from a collection of CCTV videos, one of the first articles for firearm identification A neural network and an MPEG-7-based descriptor were utilized to analyze CCTV data. For extracting features and SVM, K-Nearest Neighbor (K-NN), and ensemble tree classifiers, VGG-16 CNN architecture was used with the SVM classifier attaining over 92 percent accuracy. [10]

The Athena Safety AI System is intended to detect threats of gun homicides. The system immediately delivers a notice to the criminal suspect and relays the real-time video stream to security personnel once a threat is discovered. Zero Eyes' solution is backwards compatible with older security cameras. To preserve anonymity, it even does automatic face redaction. Its algorithm adapts over time, allowing it to improve its performance [6].

Hu et al. [15] have contributed in detecting various objects in traffic scenes by presenting a method which detects the objects in three steps. Initially, it detects the objects, recognizes the objects, and finally tracks the objects in motion by mainly targeting three classes of different objects including cars, cyclists, and traffic signs. +erefore, all the
objects are detected using single learning-based detection framework consisting of dense feature extractor and trimodal
class detection.
Grega et al. presented an algorithm which automatically detects knives and firearms in CCTV image and alerts the
security guard or operator [16]. Majorly, focusing on limiting false alarms and providing a real-time application where specificity of the algorithm is 94.93% and sensitivity is 81.18% for knife detection.

Mousavi et al. in [17] carried out video classifier also referred to as the Histogram of Directed Tracklets which identifies irregular conditions in complex scenes. In comparison to traditional approaches using optical flow which only measure edge features from two subsequent frames, descriptors have been developing over long-range motion projections called tracklets. Spatiotemporal cuboid footage sequences are statistically gathered on the tracklets that move through them.

Ji et al. developed a system for security footage which automatically identifies the human behavior using convolutional
neural nets (CNNs) by forming deep learning model which operates directly on the raw inputs [18].

Pang et al. presented real-time concealed various object detection under human dress in [19]. Metallic guns on

human skeleton were used for passive millimeter wave imagery which relies on YOLO algorithm on dataset of small
scale. Moreover, the weapon detection accuracy computed 36 frames per second of detection speed and 95% mean average precision.

Warsi A et al. have contributed to automatically detecting the handgun in visual surveillance by implementing YOLO V3
algorithm with Faster Region-Based CNN (RCNN) by differentiating the number of false negatives and false positives [20], thus, taking real-time images and incorporating with ImageNet dataset then training it using YOLO V3 algorithm.

Augdas et al. [21] shows the use of the transfer learning approach on AlexNet, VGG16, and VGG19 models to train gun and knife detection from images. The results show good accuracy, but accuracy is not a good metric to stand out the results in object detection models where mean average precision is preferred. Likewise, the model lacks the capabilities to be deployed in a real-time environment.

Jaju et ai. [22], the authors trained a model on a public dataset that used the open pose methodology for pose estimation that aids in weapon detection and improves the weapon detectors' detection capability.

Madhushree et al. [28] used Alex-net in combination with some other techniques such as spatial pyramid pooling (spp) to train a weapon detection model. However, this approach is quite old and poor since many state-of-the-art algorithms
outperform Alex-net now; therefore, it is not suitable for real-time systems.

Jesus Salido et al. [29] proposed the detection of a handgun in deep learning surveillance images by training three convolutional neural network-based models (RetinaNet, FasterRCNN, and YOLOv3) and have done multiple experiments and claimed to have reduced the number of false positives, thus gaining best recall and average precision of 97.23 and 96.36%, respectively, using RetinaNet fine-tuned with unfrozen ResNet 50 as a backbone and, later adding the pose estimation training samples in the dataset, they have achieved 96.23% and 93.36% of precision and F1 score, respectively.

Volkan Kaya et al. [30] proposed a weapon detection and classification technique by introducing a new model based on the VGGNet architecture trained on a dataset having seven different classes that include assault rifles, bazookas, grenades, hunting rifles, knives, pistols, and revolvers.

Ingle et al. [31], the authors have proposed an object detection technique for abnormal situations such as guns and knives. They have introduced a new lightweight multiclass-subclass detection CNN (MSDCNN) model to extract and detect abnormal features in a real-time scenario.

Proposed Methodology

To mitigate the issues identified in our previous weapon detector [4], this work solves those problems by having an increased number of frames per second for real-time scenarios and a reduced number of false positives. The methodology provided herein making this work successful is divided into multiple steps listed as follows:

1. Dataset selection;
2. Preprocessing operations;
3. Model selection;
4. Model training and tuning;
5. Model optimization using TensorRT network.

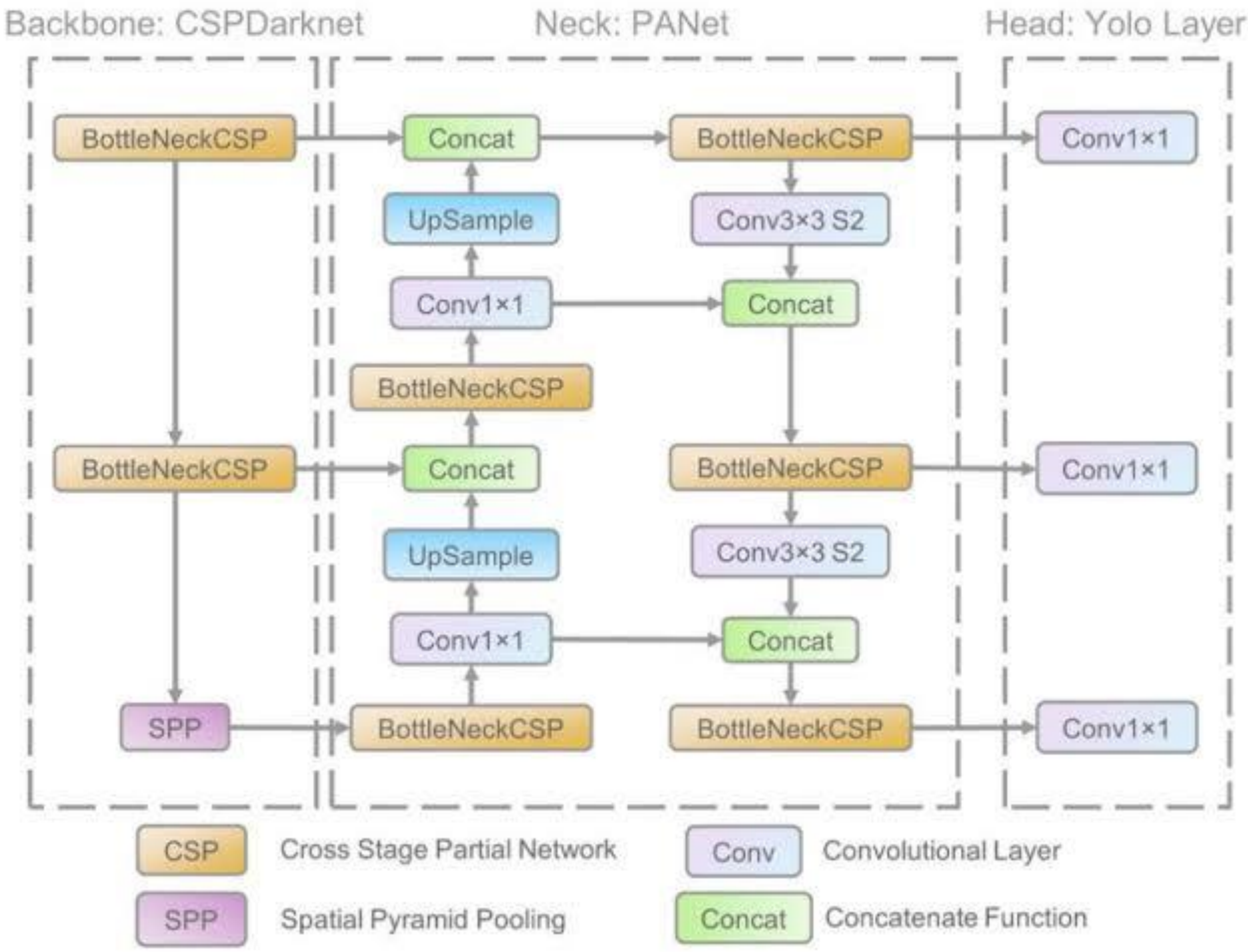
we have attempted to develop an integrated framework for reconnaissance security that distinguishes the weapons progressively, if identification is positively true it will caution/brief the security personals to handle the circumstance

by arriving at the place of the incident through IP cameras. We propose a model that provides a visionary sense to a machine to identify the unsafe weapon and can also alert the human administrator when a gun or firearm is obvious

in the edge. Moreover, we have programmed entryways locking framework when the shooter seems to carry appalling

weapon. On the off chance conceivable, through IP webcams we can likewise share the live photo to approach security personals to make the move in meantime. Also, we have constructed the information system for recording all the exercises to convey impact activities in the metropolitan territories for a future crisis. This further ends up in designing

the database for recording all the activities in order to take prompt actions for future emergency.



CONCLUSION

In this study, the state-of-the-art YOLO V3 object detection model was implemented and trained over our collected
dataset for weapon detection. We propose a model that provides a visionary sense to a machine or robot to identify the unsafe weapon and can also alert the human administrator when a gun or a firearm is obvious in the edge. This research will surely help to strengthen safety, law, and order for the betterment and security of mankind, regions of the world that have experienced significantly as a result of such terrible crimes. This will improve the economy by raising funds and tourists who are concerned about their safety and security. We focused on finding the weapon in real-time CCTV footage while minimizing mistaken negatives and positives. Subsequent work will concentrate on reducing false positives and negatives even further, as there is still potential for progress. We may try to increase the size of classes or items in the future, but the goal is to improve precision and recall.

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