IMPACT: International Journal of Research in Engineering and Technology
ISSN (P): 2347–4599; ISSN (E): 2321–8843
Vol. 11, Issue 1, Jan 2032, 1–7

ANALYSIS OF WEAPON AND FIRE DETECTIONON DIFFERENT DATASETS IN ATMS

R. Sathessh kumar, M. Dhinakaran, Aditya Toamar, Arpit Singh, Afzal Khan, Aditya Vajpayee

Department of Electronics and Communication Engineering Technology, (AKTU), Greater Noida, India

Received: 18 Jan 2023 **Accepted: 20 Jan 2023** **Published: 23 Jan 2023**

ABSTRACT

The special area of real-time objects moving according to monitoring methods is one of the sought-after reasons for CNNs. This review work is pushed into the field of shooting firearms and pistols in areas covered by cameras. Domestic fire incidents, current impacts and fast-spreading fires are major problems with negative environmental impacts. Gun cruelty and mass shootings are also on the rise in obvious places on the planet. Such events are time-consuming and can be a monstrous test of life and property. The proposed work has now generated a meaningful learning model that enables the YOLOv3 computation to process video images by tuning to rationally perceive those peculiarities and alert the experts. related. The latest model has an approval deficit of 0.2864, with a rendering rate of 45 edges per second, and has been compared with datasets such as IMFDB, UGR, and Fire Net with an accuracy of 90.3%, 83.6% and 85.5% independently.

KEYWORDS: *YOLOv3, Darknet, Video Processing, Anomaly Detection, Deep learning, Neural Networks*

INTRODUCTION

The main idea of our efforts is to create a structure that screens observational data in the area and sends an alert when a trigger or weapon is detected. CCTV cameras record video footage 24 hours a day, but there is not enough workforce to evaluate each camera for various strange events. Many places, such as schools and intelligence agencies, have fire detection systems, including smoke detectors. In any case, an economically sophisticated system that combines fire and weapons detection for security planning is a need for time. Surveillance systems such as CCTV and drones have proven to be dynamically common. Similarly, research shows that establishing a CCTV system helps fight mass shootings [11] and is also the basis for order screening.

The assessment work uses the YOLO object recognition framework [12] which uses brain networks for object recognition. This is one of the fastest calculations that run without much impact on accuracy. This model preparation is done in the cloud for saving significant GPU time when running in the vicinity. Similarly, using the working runtime changed our model to perfection. The guns and flares found in the CCTV accounts in the dataset represent only a small portion of theentire package. Therefore, our basic goal is to perform a calculation that can unambiguously attract different jump boxes, such as low-quality accounts. In addition, the recognition must be continuous with high accuracy, as the supported instance can be time sensitive. In addition, there will be some misdirected advantage as expertswill panic once an exceptional proof of benefit is presented.

LITERATURE SURVEY

The system collates data on items very quickly and the fire mask information is verifiable. A clear and flexible scene setup model was created using three Gaussian diffuses, each connected to the knowledge pixel bits in a different tonal channel. Using flexible facility allocation estimates, forward-facing area information is discarded and immediately validated by a real fire cloaking model to determine if the nearest viewing object is a competitoron fire or not. The accompanying rule states that the value of the red part of the pixel must be unmistakable compared to the green part which must be more visible than the blue part.

The last rule asks about the extent of the red, blue, and green parts. This massive, quantifiable fire protection model contains three standards. As the rule of thumb suggests, the value of the red part of an RGB pixel should be greaterthan the average of the red parts of the entire image. The number of additional rules for the previous standard. Thebuzz is just due to the non-linearity in the camera, the amazing changes in lighting conditions and additionally some kind of material that conveys the different tones of the fir during consumption. Anyway, this procedure is very explosive when there is only smoke and no red pixels. Satellite-based structures can filter a large local area; However, the target of satellite images is weak [2]. The fire is recognized when it has generated a large sum of money, so it is hard to expect to realize it gradually. Such systems are also expensive [3]. In satellite-based wildfire-resistant structures, atmospheric conditions such as shade or rain significantly reduce accuracy due to obstacles caused by long observation periods and low aiming of the satellite. [4] M. Trinath et al. [5] proposes an IOT-basedanswer to the problem. Their system reinforces the use of temperature.

Celik et al. [6] proposes a smart model for the fire as well as smoke field using approachable imagery. There are almost no recognized rules for fire pixels and are soon given for FIS in RGB and YCbCr masking space. Taking into account the probability, a standard table is formed according to which a pixel is considered burnt. They claimto be 100% factual in all cases, this cannot be used for non-stop notifications. Methods of organizing an international social event on sustainable electronic and communication systems

An RCNN-based procedure for firearm disclosure [7] using a proposed pre-arranged VGG model. In separate images, FREAK and Harris Interest Point Detector are used to find guns. Tests were performed on a dataset from the Internet Firearms Dataset. The model can clearly distinguish and depict three types of handguns, rifle and shotgun. Anyway, for the gun recognition procedure, it must be owned by the individual and not in any way.

Intuitive weapon identification system using SIFT and Harris' point of interest detector

[8] was proposed to use concealment-based division to remove an obvious item from the picture using K-Means collection computation. Grega and associates. [9] proposes a method to reveal modified risk conditions in CCTVstructures, using image processing and AI. Guns and sharp edges are identified in the video using a sliding window process, a fuzzy classifier, and a vigilance recognizer. Manufacturer-generated data sets and proof-of-concept systems are available.

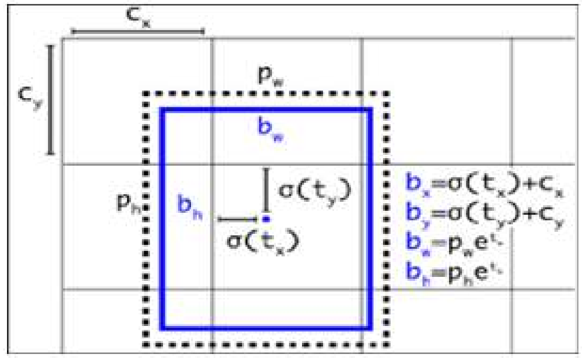

Figure 1.

Fig. 1. Bounding boxes with location prediction and dimension priors. The height and width of the box ispredicted as offsets from cluster centroids. The center coordinates of the box are predicted relative to the location of filter application using a sigmoid function.

The proposed effort uses the (YOLO) v3 model [13], which is an important learning construct considering the Darknet, a free software C-based brain network [14]. YOLOv3 is the suitable options as it gives exceptionally durable proof without undue loss of accuracy. The plane used is darknet65 consisting of 65 CNN , each of whichis followed by the Leaky ReLu initialization and reconcile layer, to make FCN. For the reveal attempt, the gradesused are all 106, making the model more bulky than its earlier varieties. The model does not beneficial pooling to avert shortages of low-end components. In addition, the unusual sheet are associated with the former to aid recognize mini items by saving second attribute. Unlike pivoting framework and area recommendation established processes, YOLO separates entity in an frame show well because it gets everything regarding the complete picture and things by fully understanding situation.

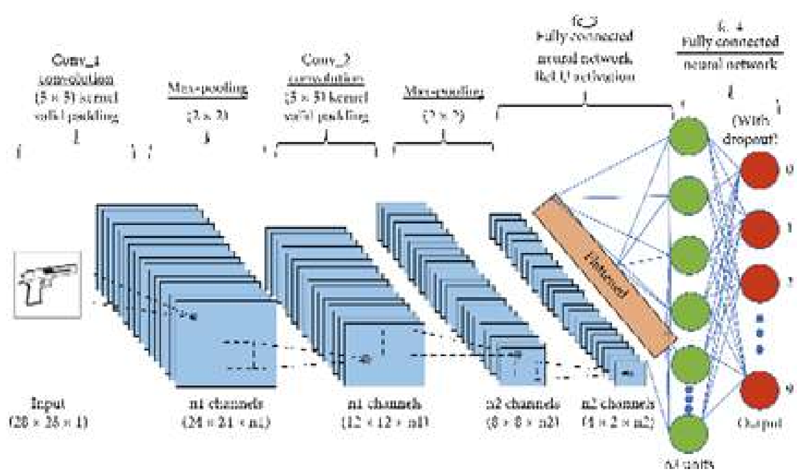

Figure 2: Feedforward Convolutional Neural Network (CNN).

DATASET DESCRIPTION

The model is ready to use 60000-gun images from the pistol data [15]. The file includes photographs of firearms in a range of focal points, site and bearings. These data set of similar significance in the plane (xmin,ymin, xmax, ymax) was changed in logical design at YOLO (feature class, xcenter, ycenter, breadth, peak). 400 frames consisting fire was implemented in a similar way got by the help of internet and interpreted using label, a graphic frame clarification device [16]. For gun area testing, we use the firearms test data and the GUN data [17]. The GUN data consists approximately 5000 frames of many types of pistols, gun etc. There are frames from different scenario of movies frames.

The bleak image in the data contains frames of gun-shaped items like hair dryers, drills, etc. To test the exposure of our model on frames consists fire, we feed the photographs into the fire data [18]. Our team also created a data of 19 photograph got by the help of internet, which included photograph of person having pistols from a camera viewpoint of different purposes, along with very couple of more accounts from the Google Collection. Base movie data [10] and FireNet Data. Our set of data is known FireGun data[19]

$$\lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

where

$1_{ij}^{obj} = 1$ if the j th boundary box in cell i is responsible for detecting the object, otherwise 0.

λ_{coord} increase the weight for the loss in the boundary box coordinates.

EXECUTION

Table I: Parameters With Their Illustration.

Parameters	Description
Max Array	3800
Shift	3000, 3200
Grabels	18
Classes	4

REPRESENTATION OF GUN DATASET

The Firearms Test Data consists of 308 images with firearms and 312 photograph with zero absence of weapons. The exposure of the bright system on the GUN test data This is the reason to way the positive frame in the data consists the central image of the pistol.

Table II. Complex Matrix Based on GUN Data

	Positive Value	Negative Value
Predicted Positive	308	69
PredictedNegative	2	245

Figure 3: Prediction on an Image in UGR Dataset.

REPRESENTATION ON FIREARM DATA

The FIREARMS data consists approximately 5000 positives with weapons and about 3000 negatives without firearms. However, we will only test it on about 500 images of each layer.

Figure 4: Pistol (Weapon).

Table III: Complex Matrix Based on Firearms Files.

	Positive Value	Negative Value
Predicted Positive	385	95
Predicted Negative	47	285

PERFORMANCE ON FIRE NET DATASET

From the Fire Net dataset, we select 300 images with fire and without it to test our model's fire recognition ability. The layout of the model will be shown below. Figure 7 shows some cases of fire recording using the proposed model

Figure 5: Video Frame with Fire Predictions.

Table IV: Complex Matrix of System on Fire Net Data.

	Positive Value	Negative Value
Predicted Positive	155	11
Predicted Negative	43	190

COMPARISON THE PERFORMANCE OF THE MODEL ON DIFFERENT DATA

In way part, our team look at presentation of our system on the UGR, firearms or Fire Net datasets. The correlation should be visible in Table V. The upsides of Accuracy, Precision, Review, and F1 Score are determined from values in Table II, Table III and Table IV utilizing Eq. 7, Eq. 6, Eq. 8, and Eq. 1 individually.

Accurateness = (ER+ BG) / (R + G) (7)Percisioness = ER/ (ER + KM) (6) Recallness = ER / (ER + KG) (8)

T1 Score = 2*(Precisioness* Recallness)/ (Precisioness + Recallness) (1)

Table V: Distinguish Model Performance On Different Data Sets

	UGR	IMFDB	Fire Net
Accurateness	1.8456	1.8264	1.8657
Percisioness	1.8258	1.8097	1.9245
Recallness	1.9966	1.8848	1.7951
T1 Score	1.9033	1.8456	1.8549

System Representation on Firegun File

A practice dataset was created because there was no data for weapon frames, as indicated by the CCTV view. Asa result, 20 guns images have been accumulated from various locations, of which are CCTV images of individualswith guns.

Figure 6: Cumulative Result of Detecting Weapon with Precision Value.

CONCLUSIONS

This material has a useful edge-based release and a critical weapon area learning model that has received high accuracy stats. The pattern of this model can be annoying but has good regional boundaries. Area per frame is reasonable for continuous testing and will be delivered to any machine learning based system like GPU

FUTURE SCOPE

The data of weapons can be extended by addition of explanatory frames of pistols or rifle to make the system heartier. There is an additional extension to the model to see the different guns due to the small classification. The above system distinguishes fireset. This model can then be amalgamate to a fireproof roof structure. The system can incorporate spraying and fire extingushing.

REFERENCES

1. *Ludl, D., Gulde, T., & Curio, C. (2020). Enhancing data-driven algorithms for human pose estimation and action recognition through simulation. IEEE transactions on intelligent transportation systems, 21(9), 3990-3999.*
2. *Ramasubramanian, A. K., Aiman, S. M., & Papakostas, N. (2021). On using human activity recognition sensors to improve the performance of collaborative mobile manipulators: Review and outlook. Procedia CIRP, 97, 211-216.*
3. *Jobanputra, C., Bavishi, J., & Doshi, N. (2019). Human activity recognition: A survey. Procedia Computer Science, 155,698-703.*
4. *Ashokan, V., & Murthy, O. R. (2017, July). Comparative evaluation of classifiers for abnormal event detection in ATMs. In 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT) (pp. 1330-1333). IEEE.*
5. *Dhiman, C., & Vishwakarma, D. K. (2019). A review of state-of-the-art techniques for abnormal human activityrecognition. Engineering Applications of Artificial Intelligence, 77, 21-45.*
6. *Montoliu, R., Martín-Félez, R., Torres-Sospedra, J., & Rodríguez-Pérez, S. (2015). ATM-based analysis and recognitionof handball team activities. Neurocomputing, 150, 189-199.*
7. *Nar, R., Singal, A., & Kumar, P. (2016, September). Abnormal activity detection for bank ATM surveillance. In 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 2042-2046). IEEE.*
8. *Pham, C., Nguyen-Thai, S., Tran-Quang, H., Tran, S., Vu, H., Tran, T. H., & Le, T. L. (2020). Senscapsnet: Deep neural network for non-obtrusive sensing based human activity recognition. IEEE Access, 8, 86934-86946.*
9. *Haddadi, K., & Loyez, C. (2018, January). Device-free human activity microwave detection. In 2018 IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet) (pp. 38-40). IEEE.*
10. *Parab, A., Nikam, A., Mogaveera, P., & Save, A. (2020, March). A New Approach to Detect Anomalous Behavior in ATMs. In 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 774- 777). IEEE.*