IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

TRANSFORMATIVE SOLUTION FOR VIOLENCE IDENTIFICATION

[1]Venkatachalam G, [2]Mr. Giriprasath. KS,
[1]M. Sc Data Science and Business Analysis, [2]Assistant Professor,
[1 2] Department of Computer Science,
[1]Rathinam College of Arts and Science, Coimbatore, India

Abstract : The average yearly death toll from acts of human aggression worldwide is 7.9 per 10,000 individuals.The majority of these acts of violence against people occur suddenly or in remote places.One of the most interesting and difficult study areas in computer vision is violence recognition. Findingviolence using surveillance cameras in public and private spaces is one of its unique uses. We demandthat these violent incidents be immediately under control. They must conduct a thorough search for automated violence detection systems because human operators are required to monitor the surveillance video screen, which frequently results in mistakes and neglects to identify the occurrence of unexpected events. One of the main obstacles to halting these activities is the information delay in this case. In this work, the detecting technique is employed to thrive on this issue. One of the best computer vision algorithms is the one that uses CCTV to detect moving things. These days, CCTV cameras are installed on every street and are quite useful for case solving. Certain deep learning algorithms are applied in computer vision to anticipate and identify actions and attributes in videos. When police arrive at dangerous locations in real time, they analyse CCTV footage and begin an investigation before moving further. The purpose of this study is to consciously identify violent crimes seen on CCTV. Several uses for gathered video features are made possible by the use of computer vision and machine learning techniques, one of which is safety monitoring. The effectiveness of violent event detection is determined by how accurate and efficient it is. We describe a unique architecture for video surveillance camera-based violence detection in this study. The Yolo v8 models identify the usage of weapons in the incident, as well as the violent act. These deep learning models constitute the basisof the work and are utilised to create a video detection system. Real-time software or an application programming interface (API) can be created using this concept. According to the study's findings, the suggested model has a 74% accuracy rate.

***Index Terms* - Closed-circuit television (CCTV),Human violence, deep learning, Machine learning, Transfer learning..**

1. Introduction

The technological improvement in video and image processing to locate the contents for a variety of applications, including identifying actions and objects they employ, like knives or firearms, technological advancements in video and image processing have been remarkable [1]. It is only because human aggression has increased in our everyday lives that the ability to identify activities from video streams has improved in recent years. The surveillance footage is typically found through manual means. Despite the low rate of human violence, there are millions of cameras installed worldwide, therefore hazards can arise anywhere. With regard to deep learning techniques and approaches, this is an estimation of the present state of human-violence systems. With the use of the data collected, we may combine this technology with others to identify instances of human aggression that take place on a daily basis [2].

Violent behaviour is automatically detected by deep learning systems. This method goes through several phases, including classifying videos, detecting objects, and detecting actions [3]. Our goal is to develop a system that can identify violent behaviour even in the absence of people. To identify the human violence and items in the movie, Yolo - v8 object and face identification model and Google Net - Inception - v3 image classification model employ transfer learning [4]. The machine learning pre-trained model Inception - v3 is employed in this investigation. It is superior to the fundamental design of the Inception v1 and v2 C.V. models. The Inception - v3 models have additional information to retain inceptions to upper layers and are trained on image net datasets. When it comes to object detection, the Yolo v8 model offers a low mistake rate and a high accuracy rate. Yolo v8 has detected over 80 distinct labels, showing improved accuracy over Yolo v4's detection.

2. Methods and Materials

Visual surveillance systems' ability to recognise individuals aids in the global identification of security-related issues [5, 6]. The number of people in an odd film or a video involving human violence is determined using the deep learning model. Deep learning models are used in human violence detection tasks, while different object detection models are employed in object detection tasks. The provided video frame will be classified as either violent or non-violent, and it will be stored in the database. utilising faster learning algorithms and classification approaches, it is possible to detect violence utilising large populations and high- dimensional data. Once the violence is identified, the system is alerted [3]. Violence can be detected more precisely than with the prior IVF method thanks to the enhanced Fish vector and the sliding window approach, which takes into account the spatiotemporal positions of the violent acts. As a result, violence detection happens far more quickly [7]. To accurately detect objects, dilated convolution and 1x1 convolutional layers are encapsulated as a single one using the YOLO – v3- MT model and AS– CBAM [4]. In the relevant datasets, motion detection algorithms can be applied to automatically detect the violence. The Mosift algorithm is mostly employed for violence detection. These enable the system to display events in real time and trigger fights when they happen [8].Weapons such as hunting knives, revolvers, pistols, and hunting rifles can be identified with the use of the VGG net and ResNet-50.A better detection model is produced by gatheri ng images of these weapons from sources, training t hem, and testing them [1].In this work, we employ the Inception v3 and Yolo v8 models for a single goal, which is to identify the items and violent acts that are occurring. The goal of using two distinct model is to achieve superior outcomes. These two models were applied to further distinct goals in earlier works, but in this project, we merged them (as an API) to achieve our goals. Various data sources were gathered in order to produce effective outcomes.

2.1 Deep Learning

It's a whole intersection point of artificial intelligence, where artificial intelligence (AI) is the key base platform for deep learning. The term derives the nature of studying everything in detail form for analysis and conclusion. Humans can do a handful of operations and analyses at a certain time only, if the quantity is less means the data is less, imagine something we humans want to get some detail to report for 100000 text which is highly impossible and takes huge time. For these issues, we can build a model to understand and absorb the learning information after which the model can do some operation to give the required results and conclusion. Deep learning is the operation done with machine learning techniques that makes the supervised and unsupervised function effective. It talks about the model construction and the inner architecture. We can access these techniques using a python programming language which is open-source software. These techniques have a mathematical concept behind them and change all the theoretical matter to numerical concepts to understand all the relationships between all the information. Python has various open-source functions where all the mathematical operation changes into py function and it can be used via packages.

2.2 Packages

A unit word that contains py function which can be mathematical, statistical, word processing, or binary action. These packages reduce the time to construct the model and architect the networks, to install the packages we use !pip command. NumPy:An initial Python code that includes all the fundamental functions needed to manipulate numbers and access binary data.

Pandas: If your working data is in a structured form that needs to be added to the constructed model, pandas will help them to the convection process.

OpenCv: A computer vision package that helps in reading images, converting video into data frames, and also saving video or images in any format.

FastAPI: A web framework that supports Python RESTful API development. With the help of this, the developed model can be implemented on any website as API.

2.3 Neural Networks

Neural networks exactly imitate the process of a neuron. This neural has Input layer, hidden layer and output layer. Neural networks work with several processes of layers that are known as the perceptron. This method is applied in many different domains, including detecting systems and forecasting.

2.4 Transfer Learning

Using pre-trained modelling, this strategy reduces a great deal of computational knowledge. So, using deep learning models is a common thing to do with pretrained for challenging models [9]. Natural language processing tasks that accept text as input are most frequently used in transfer learning. In higher starts, the starting skill on the source model ought to be greater than the other.

2.5 Pre-trained Model

It takes some time to build a new high- performance model, and it takes effort to add the mathematical function to networks.,we know by transfer learning we can append the features from one model to another model. Some so many open- source models will have the same motivation and techniques, so we can take the required feature function for building our model.

2.6 Yolo – v8

YOLOv8, or "You Only Look Once version 8," is an advanced and state-of-the-art object detection system used in computer vision and image analysis. It builds upon the YOLO (You Only Look Once) series of real-time object detection models. The YOLOv8 model is designed to quickly and accurately identify and locate objects within images or videos, making it an invaluable tool for a wide range of applications, including autonomous vehicles, surveillance systems, and various forms of image and video analysis. YOLOv8 is renowned for its efficiency, allowing for rapid object detection without compromising on accuracy. It employs deep learning techniques and neural networks to achieve this, with the capability to detect and classify multiple objects simultaneously. The model can work with various object categories and is highly versatile. One of the key features of YOLOv8 is its ability to operate in real-time or near-real-time, which is vital for applications where speed is of the essence, such as autonomous driving or video surveillance. This efficiency is achieved through a single forward pass of the neural network, which distinguishes it from other object detection methods.

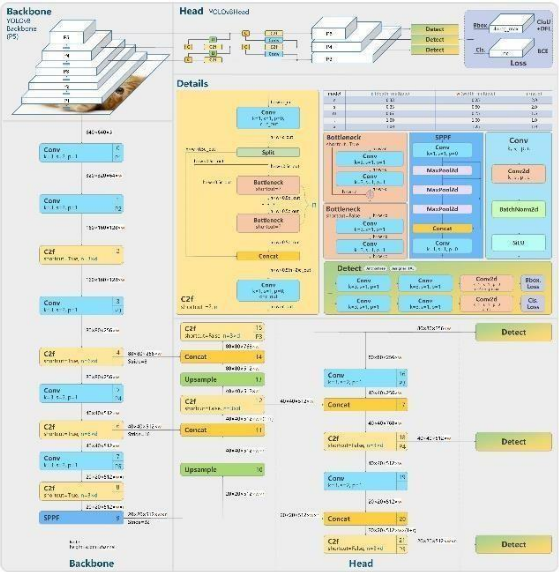


FIGURE 1. Architecture of Yolo – v8 model.

2.6.2. Model Junction

To connect the Head and Backbone this layer does that job, it plays the role of a bridge to join the input and output layers. PANet architecture helps to access the breaking point of the images and plays a vital role in the spatial information convention. The weights can be properly aligned and it can be segmented pixel vice. Bottom-up Path Augmentation is the first layer of the planet. While heavy access to the data, may lose the features, there is a chance of spatial data to decrease, and pixel range cannot be detected properly in the next layer, accuracy may also dropdown. To reduce the previous problem the PANet gives the solution of joining the enriched features in a structured manner with the connection of localization data. The layers should be more in number to avoid the long sensitive spatial data. The lower layer has a connecting line segment that joins to exchange the weights and creates shortcut paths. In the next part of the layer, the shortcut leads is Adaptive Feature Pooling, where all the spatial data will reduce its pixels, These higher-level data will be compressed and the function will take place in both the layers, the pooling method is max pooling there, it will get the max weights and divide by the average of it, this a one by one process where each element in the weight box will go through this process. The fully connected layer is to prepare the data for the final prediction process, this will check and control the segmentation process, and the parameters may affect the spatial data and control flow. The rate of distribution of spatial data is the same in all three layers.

2.6.3. Model Head

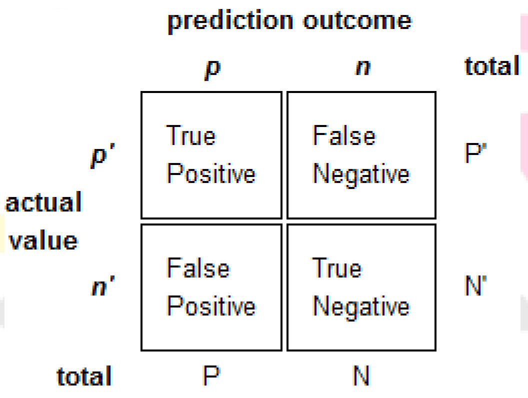
The head plays the role to find the prediction answer and the output will be in the matrix form, we need to get it has probabilities values for humans to understand it, it gives the bounding boxes to understand the detected areas. For this feature pyramid network (FPN) is allied in the structure. The FPN is pyramid- style layer construction. It is like long short- term memory (LSTM) the process will go from downwards to upwards, this pathway structure maintains the increase and decreases the flow of spatial segmentation. The detector will have the absorbed features maps and will have a designer role in the output prediction, while the images in feature extraction the area with the object will be identified as objectless detection and it also has an imaginary boundary box. This FPN is faster than all recurrent neural network (RNN) and LSTM.

2.7 Inception - v3 – Human Violence Detection

In this study, Inception - v3 is used as the base model. Inception - v3 is a version of the Google Net model developed by Google for image recognition and classification. Inception – v3 consists of 42 layers and a lower error rate than its predecessors. It has 5 convolution layers, 1 Conv padded layer, 3 Inception layers, and 2 pooling layers with the activation output as ‘softmax’. It takes the input dimension as 229x229x3. After passing through two layers it gives the output as the dimension of 8x8x2048. Using the ‘softmax’ as the classification activation function, it gives the final output as 1x1x1000 (Table 1).

2.8 Confusion Matrix

After building up the model and getting the required result, we need to find whether our model is giving a good result or not. For that we can use a confusion matrix to get the accuracy and the confusion matrix shows the results rate of the models trained [10].



		prediction outcome		
		p	n	total
actual value	p'	True Positive	False Negative	P'
	n'	False Positive	True Negative	N'
total		P	N	

Figure 2. Confusion matrix.

Figure 2 shows that

- Predicted data are denoted as rows
- Actual data are denoted as columns
- The variable value can be either positive or negative
- True Positive: The actual data is positive but predicted as positive
- True Negative: The actual data is negative but predicted as negative
- False Positive: The actual data is negative but predicted as positive
- False Negative: The actual data is positive but predicted as negative

Using the obtained value, the accuracy of the modelling can be found using Equation (1). Recall tells the number of positive predictions that were made out of all positive predictions (Equation (2)). Error rate tells the incorrect prediction of the model in percentage (Equation (3)). If the error rate is less it is set to be the model is performing efficiently.

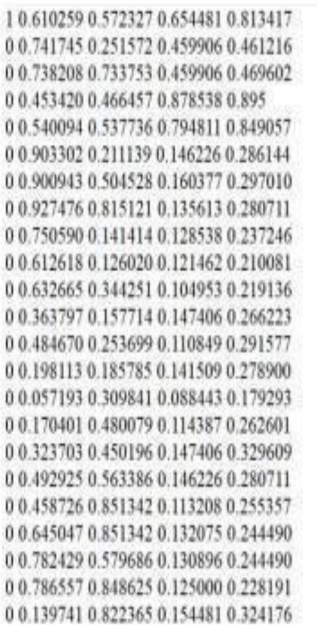
$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Error\ rate = \frac{FP+FN}{TP+FP+TN+FN}$$

3. Data Analysis

Data Set The data are in the .jpg format for training and testing our model. For the Yolo -v5 model we should have data of the detected objects in pixelated form. As it is supervised learning, label data is also needed. First, the images of objects like weapons, other objects are collected from different sources and some also from Kaggle. For person detection, the personal



```
1 0.610259 0.572327 0.654481 0.813417
0 0.741745 0.251572 0.459906 0.461216
0 0.738208 0.733753 0.459906 0.469602
0 0.453420 0.466457 0.878538 0.895
0 0.540094 0.537736 0.794811 0.849057
0 0.903302 0.211139 0.146226 0.286144
0 0.900943 0.504528 0.160377 0.297010
0 0.927476 0.815121 0.135613 0.280711
0 0.750590 0.141414 0.128538 0.237246
0 0.612618 0.126020 0.121462 0.210081
0 0.632665 0.344251 0.104953 0.219136
0 0.363797 0.157714 0.147406 0.266223
0 0.484670 0.253699 0.110849 0.291577
0 0.198113 0.185785 0.141509 0.278900
0 0.057193 0.309841 0.088443 0.179293
0 0.170401 0.480079 0.114387 0.262601
0 0.323703 0.450196 0.147406 0.329609
0 0.492925 0.563386 0.146226 0.280711
0 0.458726 0.851342 0.113208 0.255357
0 0.645047 0.851342 0.132075 0.244490
0 0.782429 0.579686 0.130896 0.244490
0 0.786557 0.848625 0.125000 0.228191
0 0.139741 0.822365 0.154481 0.324176
```

Figure 3. Example of Yolo label data.

images and random faces of the persons from different sources were collected. Google images are also used to collect random person images [1]. To collect huge data with the required custom image sizes and quality, we are adding a chrome extension called imageeye (image downloader) which has a control function feature where we can adjust the size of the picture and it will download all the images in a full one google search entity. For better quality add a size range from 1300 - 2500 for both the height and width of the picture [11].To label images, a software called labeling is downloaded in python, which will create a label with their pixel ranges. Use !pip install labeling command, which will download it in the Linux interface. Open the labeling software and add the folder which contains your images. Using the Rectangle Box command, mark the area of the object which you need to label. In our case, we have 4 labels, 2 labels of weapon images, and another 2 labels of people images. After labeling all the images the file is exported as XML, but the needed format of the output pixel file is .txt extension, labelling does not have the preferences to change it. For this XML to .txt process, a small python code script is executed, which will change the file and make the information according to the required form for our Yolo - v5 model. There are more than 500 images are collected and labelled. Figure 3 shows the example of the Yolo - v5 data .txt file, the python converts images from XML to .txt successfully. For human violence detection, real action videos are used. Real- time fight videos that have been recorded in CCTV, clips from movies, and small fights held during games and public gatherings are collected from different sources [12]. There are more than 100 videos collected with different formats like mpg, mp4, .avi, etc. All these videos are converted to images to train a detection model. The collected videos are separated into two folders as violence and non- violence. To train the models with videos as data first we have to convert the videos into images. OpenCV, a computer vision package that helps to read videos and also convert them into images is used. First, the collected videos are converted into images from each frame of the video. If a video runs around 1 minute, it converts that into 30 images with a count of a timeframe gap, which is saved into separate folders as human violence and non-human-violence. Like this process all the collected videos are converted into images, there are more than 10,000 images obtained as shown in Figure 4. With these data frames, the model is trained and tested. The converted images are pre-processed; as our model takes input with a dimension of 229x229x3 here the dimensions of the image are resized using the cv2.resize function.

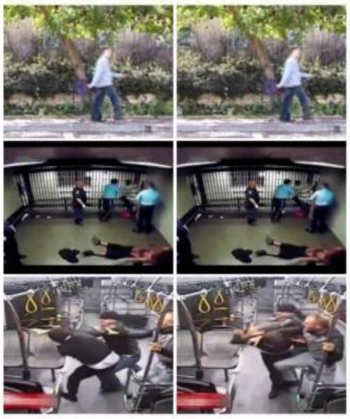


Figure 4. Subplot of image of human-human violence and non-human violence

Working in Google colab will give us free GPU. GPU increases the speed of rendering and compiling time. A huge amount of data which is not only in the numerical form will enhance huge amounts of steps to execute, GPU interface produces graphical base processor and evaluation of this is in unit type. Following procedures are followed: Open colab using google account. mount the collab with google drive to produce floating hardware. For the transfer learning part, we cloned the Yolo - v5 model from an open- source website. We made a duplicate file and stored it in the working directory, checking the requirements for extracting features from this model. Import torch packages, which will give data assessing, function for both numerical and graphical representation, this torch function is built to perform in GPU interface. For checking the version of the packages, requirements.txt will print the availability and required version for all the functions. Now go to your data, open a new folder, create a subfolder called images, and label, inside that both the folders add train and Val subfolders. Write a python code with for and if conditions to divide the train and test set for our data. 80 percent of data should be a trained dataset and the remaining 20 percent will be testing our model. A huge number of datasets will yield a high-performance model.The extension of both .jpg and .txt should have the same name only, after splitting, check the data are placed correctly in the correct folders. Now go to the config file and create model metrics. Certain keywords functions determine the running and building of the model. we have 4 classes for our model, open the config file and add classes like 4, Batch size as 8000, the calculator part of the batch size is classes * 2000, step size has the max size to 90 percent of batch size that means 7200, min size has 80 percent of batch size that is 6400. Go to the backbone layer here to construct the filter size according to the classes and the filter formula is (classes + layers) *construct three layers.The remaining numerical values can be determined by filter values. We are uploading the test files so predication is directly done here, for training the data, constructing a code, and saving it as train.py in the model file.Train code creates a model with hidden layers and activation functions. Here the learning part takes place. We are creating a work base and asking the model how to learn, what kind of features it should learn from the datasets, and pre-trained model features. Access this tain.py file using !python function and declare the epochs and batch count to it, epochs defines the iteration number how many times the model should learn the process, learning for so much time the model will learn the given information deeply which will be useful for yielding high accuracies. Install the tensor board function to visualize the data to find performance metrics. This Val data goes to the testing part, attached to the predicating measure so we can check the predicated objects. It automatically saves the weights and testing data in the run folder, where we go check the data to check how well it predicated our objects. The converted images from two separate folders are imported. All these images are appended as a single list and labels for the classification are also mentioned in the list as [‘fight’, ‘no fight’] [13]. The dataset (framed images) is split into train and test data using the train_test_split. The InceptionV3 model is imported and then it is considered as the base model. With the help of base, a new layer of Global Average pooling is added to make the output as 2 label classification, i.e, human violence, not human-violence. The activation function of the model is given as ‘sigmoid’. The model is compiled with the loss as ‘binary _cross entropy’. Accuracy metrics are also obtained. The model is fitted with the train data and test data with verbose=1, epochs=25, and batch size =64. The model resulted in 74.% of accuracy. The trained model is saved in ‘pickle’ format [12]. Now using the pre- trained model, we can predict the new videos. As Inception V3 can only be used for image classification, to classify a video, it should be converted as image frames. Using cv2 the video to be predicted, can be converted into images [14, 15]. The image classification model is slightly modified with the help of cv2.

4. Results and Discussion

An extensive way of developing a technique related to automatic surveillance video detection is to recognize if there is any human violence that has taken place or not. Hence, the best way to identify this is using a deep learning models. It is more important to develop a model to recognize and to detect human violence. The convolutional neural network is used to pre-train the model. Using long short – term memory that uses fully connected layers. Along with CNN that is used to analyze the local motion in the video. The model is built using the features of yolov5 architecture and custom neural networks, the train, and test data are fitted and the expected results are obtained from it. The obtained results are to be examined now using the classification metrics. The common metrics used are accuracy, confusion matrix, F-score, precision and recall. The confusion matrix with normalization and without normalization helped to define the accuracy of the model. As mentioned earlier each classification model is built and fitted with test values. The final accuracy for the object obtained is 74%. This Val data goes to the testing part, attached to the predicating measure so we can check the predicated objects. It automatically saves the weights and testing data in the run folder, where we go check the data to check how well it predicated our objects. Figure 5 shows the boundary box and the label classes for prediction test images and prints a person's face with their class name.

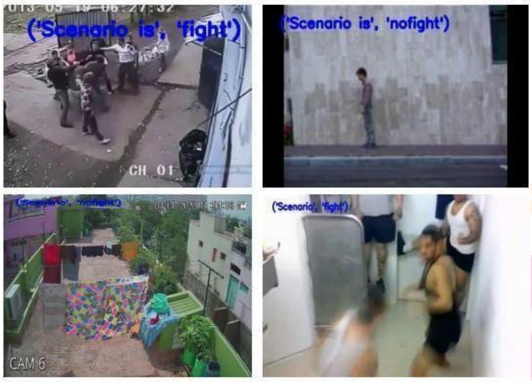


Figure 6. Predicted output from the captured video frame.

The model is trained with the Inception - v3 model and also modified video classification is used. With help of a modified classification script and base model, the test video is successfully classified with an accuracy of 74%. Here the live detection implementation is also applied, that is either from the source camera or web camera the streaming video will be converted into data frames and predicted as shown in Figure 6. The future work of this study has an idea of implementing the database as backend. That is the video to be predicted is uploaded which gives results as human violence or non-human violence, also the object detects are stored into database. Also, an additional feature to be added into the website that includes report generator. If the user wants to generate a report its results the detected objects or faces that have been already present in the database. If it is already in the database, it shows, time and date when the detected images are stored. It will provide a complete report of objects detected, no. of faces detected and whether the detected faces have already existed in the database involved during human-violence or non-human- violence scenario. The limitations of this study are it lags in processing the detection of objects, i.e., it takes time to recognize objects in the video.

5. Conclusion

In this study, a model that helps in human- violence detection and also detection of faces and objects is developed. These two different models were converted as a pickle file which is imported into the local website that has been created using the CSS/HTML as front end.The FAST API web framework helps in combining these deep learning models and implementing them in the website. On this website, there are two buttons provided, one for the human-violence detection model another one for the object & face detection model. Using these, the uploaded video results in either it is human-violence or nonhuman- violence and another button option is provided which helps to detect the objects, faces in the video.

References

[1] Kaya V, Tuncer S and Baran A 2021, Detection And Classification Of Different Weapon Types Using Deep Learning. Applied Sciences, 11 (16), 75351-6.

[2] Singh P and Pankajakshan V 2018 A Deep Learning Based Technique For Anomaly Detection In Surveillance Videos. Proc. of the 24th National Conf. on Communications, pp. 1-6.

[3] Dandage V, Gautam H, Ghavale A, Mahore R and Sonewar P A 2019 Review Of Violence Detection System Using Deep Learning. Int. Research Journal of Engineering and Technology 6 (12), pp. 1899-1902.

[4] Wang K, Liu M 2022 YOLOv3-MT: A YOLOv3 Using Multi-Target Tracking For Vehicle Visual Detection. Appl. Intell. 52, pp. 2070–2091.

[5] Antoniou A and Angelov P 2016 A General Purpose Intelligent Surveillance System For Mobile Devices Using Deep Learning. Proc. of the Int. Joint Conf. on Neural Networks, pp. 2879- 2886.

[6] Savran A 2007 Multifeedback-Layer Neural Network. IEEE Transactions on Neural Networks, 18 (2), pp. 373-384.

[7] Bilinski P and Bremond F 2016 Human Violence Recognition And Detection In Surveillance Videos. Proc. of the 13th IEEE Int. Conf. on Advanced Video and Signal Based Surveillance, pp. 30-36.

[8] Fu E Y, Leong H V, Nga G and Chan S 2016 Automatic Fight Detection In Surveillance Videos. Proc. of the 4th Int. Conf. on Advances in Mobile Computing and Multimedia, pp. 225-234.

[9] Manoharan S 2019, Image Detection Classification And Recognition For Leak Detection In Automobiles. Journal of Innovative Image Processing, 01 (02), pp. 61– 70.

[10] Kim J H, Song J H and Lim D H 2020. CT Image Denoising Using Inception Model. Journal of the Korean Data And Information Science Society, 31 (3), pp. 487–501.

[11] Bhargav P, Sree Lakshmi Keerthi B S L, Charitha K, Sarath B and Pratap A R 2020 Face Clustering On Image Repository Using Convolutional Neural Network. Int. Journal of Psychosocial Rehabilitation, 24 (5), pp. 5104– 11.

[12] Fauzi F, Szulczyk K and Basyith A 2018 Moving In The Right Direction To Fight Financial Crime: Prevention And Detection. Journal of Financial Crime, 25 (2), pp. 362– 368.

[13] Du S, Zhang B, Zhang P, Xiang P and Du H 2021, FA-YOLO: An Improved YOLO Model For Infrared Occlusion Object Detection Under Confusing Background. Wireless Communications and Mobile Computing, 1896029.

Sharma J, Giri C, Granmo O C and Goodwin M 2019 Multi-Layer Intrusion Detection System With Extratrees Feature Selection, Extreme Learning Machine Ensemble, And Softmax Aggregation. EURASIP Journal on Information Security, 15.

[14] Xu B 2021 Improved Convolutional Neural Network in Remote Sensing Image Classification. Neural Computing and Applications, 33, pp. 8169–80.