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NetApps Approach for Accelerating Vertical Adoption of 5G Networks: A UAV Case

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***Abstract*—Whilst the Fifth Generation (5G) mobile networks are being deployed worldwide, the adoption of this next-generation networking paradigm by the vertical businesses such as the 4th industrial revolution (Industry 4.0) sectors is lagging. One of the empirical barriers for the verticals to embrace 5G rapidly is the lack of easy-to-access platforms that facilitate cost-efficient deployment of their Network Applications (NetApps) to create end-to-end services. This paper presents a novel and realistic NetApp platform to remove this barrier, thereby speeding up the smooth vertical businesses' transition to 5G and beyond networks. Particularly, the paper provides a vision and insights on an innovative Unmanned Aerial Vehicle (UAV) based Industry 4.0 NetApp to cast lights on how 5G NetApps can help shape the resultant new business models and open new business opportunities. In this case, the NetApp is able to improve the results by detecting intruders in real time and reducing the delay of detection by 226 ms (38%).**

***Index Terms*—NetApp, Object Detection, UAV, Intruder Detection**

I. Introduction

The 4th industrial revolution (Industry 4.0) combines physical and digital technologies under connected system infrastructures to improve efficiency in manufacturing productivity and quality, work safety, environmental protection, and supply chain optimisation. The realisation of Industry 4.0 relies on not only locally installed smart Internet of Things (IoT) monitoring and automated control technologies, but also the combination of emerging technologies over smartly interconnected and collaborating infrastructures. The Fifth Generation (5G) mobile networking is a key enabler to meet the strict networking requirements set in Industry 4.0, allowing the launching of Network Applications (NetApps) tailored to the infrastructure capabilities and the requested service provisioning requirements. This is an essential requirement for 5G and beyond networks, which should support the user-centric approach for the Industry 4.0 industries in the creation and management of their own digital services, along with the independent growth of the other existing and emerging stakeholders such as 5G network operators, who are typically also the infrastructure owners, the NetApp developers and so on. Towards this direction and in addition to the design and development of 5G platforms and ecosystems that enable infrastructure virtualisation and support of edge processing, smooth and cost-efficient porting of NetApps in 5G ecosystems needs to be supported too, thereby making the Industry 4.0 sector (and in principle any emerging vertical sectors) ready to exploit its full potentials, such as production automation, robotics technologies, smart logistics and metering. The successful porting of NetApps requires attracting vertical service developers and providers (being currently mostly activated in the cloud), and their enhanced ability to easily deploy new tailored features, such as performance monitoring and optimisation, cognitive decision making and enhanced cyber security capabilities. In turn, the challenging performance and operating requirements of the new class of NetApps should be efficiently supported by the underlying platform, embracing recent well-known technologies, like Network Functions Virtualisation (NFV) and Multi-access Edge Computing (MEC) that transform network operators' infrastructures into distributed data centres with advanced virtualisation and software-driven capabilities.

To achieve the above vision, several projects have been launched recently, especially those by the European Commission. For instance, VITAL-5G targets to showcase the benefits of 5G-based NetApps using real-life trials over state of the art vertical facilities (warehouse, hubs, ports) and advanced European 5G-testbeds [1]. 5G-EPICENTRE [2] employs cloud-native 5G infrastructure and NetApps for public protection and disaster relief. In [3], Smart5Grid introduces a 5G solution for supporting integration, testing and validation of existing and new 5G services and NetApps from third parties for smart energy grids of the future. In 5G-ERA [4], use cases from four vertical sectors including public protection, disaster relief, transport healthcare and manufacturing will be validated by prototyping NetApps solutions using 5G technology. In 5G-IANA [5], a 5G open experimental platform for the

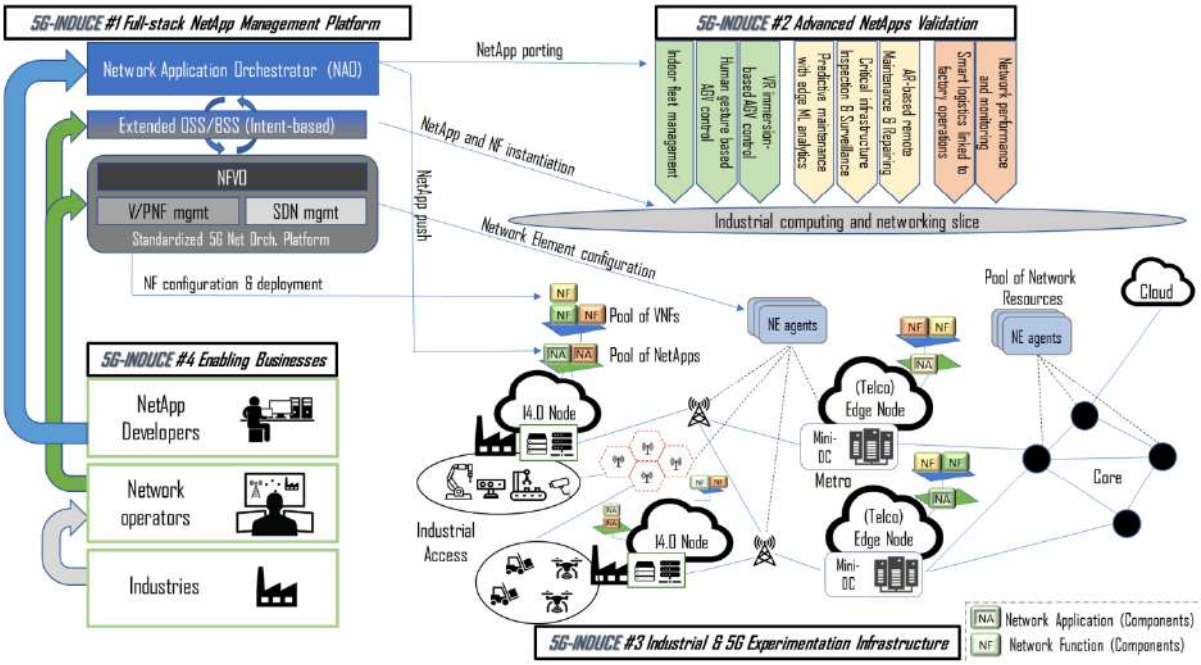

Fig. 1. Overall vision and the adopted approach of easy (i) porting and/or (ii) development of industry 4.0 NetApps over advanced experimentation facilities combining real 5G and private industrial networks.

automotive sector will be developed to provide computer and communication infrastructure, management and orchestration components along with advanced NetApps specified for this sector. All these projects shed light on the importance of having easy-to-access platforms and cost-efficient deployment for the creation of end-to-end business services over 5G networks. The work reported in this paper reflects the a new NetApp architecture in the 5G INDUCE project [6], which emphasises Industry 4.0 NetApps and leverages Unmanned Aerial Vehicle (UAV) platforms.

The remainder of the paper is organised as follows. Section II defines the NetApps and its overall vision. Section III describes the NetApps architecture and main components. Section IV highlights UAV based Industry 4.0 NetApp, and the corresponding experimental results are presented in Section V. Section VI concludes the paper.

II. Definition of NetApps

A NetApp comprises a set of networked Virtual Network Functions (VNFs), together with the required resources, deployable and operating over 5G and beyond networks, distributed across the various end-to-end network infrastructure including edge, core network and so on. The VNFs in a NetApp are typically developed by vertical business service developers for particular vertical use cases, and thus they are different from the network VNFs (such as those 5G system data plane and control plane VNFs: UPF (User Plan Function), Access and Mobility Functions (AMF), Session Management Functions (SMF), etc.) usually developed and deployed by network service providers and/or network operators. However, a NetApp does not exclude additional VNFs (and even Physical Network Functions (PNFs)) from the service provider and/or network operator in order to enhance its operation and or performance; examples may include encryption and decryption VNFs for secure communications, video processing VNFs and so on. There are three types of VNFs: customer-facing service VNFs, network-facing (3GPP) VNFs, and value-added middleware VNFs. A NetApp can be deployed on demand as requested by a vertical user, by a network operator or a service provider in conjunction with a network operator, depending on the business models. A NetApp should be cloud-native to allow automated cloud-based deployment; it can operate over a network slice. A NetApp may have embedded edge intelligence in its edge VNFs to benefit from MEC. For AI-based critical missions, a NetApp requires low end-to-end latency to enable real-time procedures and cognitive application reaction. A NetApp should be compatible with private 5G and beyond networks, and hybrid private and public 5G and beyond networks.

III. Architecture for NetApps

The proposed NetApps architecture in the EU 5G INDUCE project [6] is shown in Fig. 1. This NetApps paradigm allows separating various business roles in an ecosystem, including (5G) network operators, industries (e.g., Industry 4.0 businesses), and NetApp

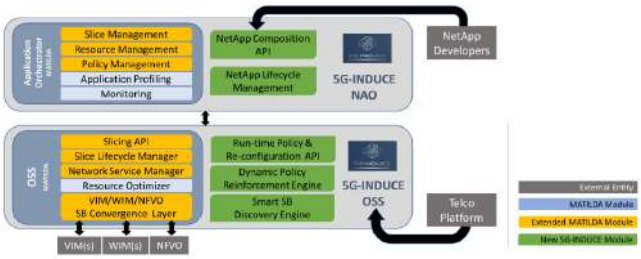

Fig. 2. Structure of the NAO and OSS and extensions/additions of components in support of the NetApp developers.

developers. It features four pillars, including a full-stack NetApp management platform for facilitating the composition and deployment of Industry 4.0 NetApps over 5G networks, advanced NetApps validation for validating the diverse industrial NetApps (e.g., UAV-based NetApps for critical Industry 4.0 infrastructure inspection and surveillance, network performance and monitoring etc.) on boarded by industries, industrial & 5G experimentation infrastructure for pre-deployment testing, and enabling businesses for allowing the various business roles to collaborate. As shown, network functions belonging to an NetApp can be distributed over the different network segments/nodes in the industrial & 5G infrastructure to create end-to-end business services.

Network management is typically owned by the network operator, who is reluctant to expose any infrastructure details to end users; however, industries require such information for optimised business application deployment. Thus, an advanced Operations Support System (OSS)/Business support systems (BSS) provides the interface that translates NetApp requests into network connectivity and resource allocation requirements. The NetApp Orchestration (NAO) is integrated with the OSS, extending its capabilities to the interfacing with the industrial and the NetApp developers, while the network operator gains the ability to apply polices and any intelligent data analytics at the service level. This scheme maintains the edge resource management capabilities of the standardised ETSI NFV Orchestration (NFVO) framework that manages the distributed resources over the virtualised infrastructure. NFVO then enables an application-oriented network management and optimisation approach. We adopt this two-layer orchestration approach, as shown in Fig. 2, which clearly separates the application orchestration from the OSS processes. This enables developers and industries to create and manage respectively the NetApps that are requesting deployment over the network orchestrator, which in turn undertakes the placement of the VNFs (application and network) on the available resources following the requests (intents) of the NAO. The NAO provides an API to NetApp developers for NetApp composition, and it manages its lifecycle. The prototyping of this orchestration solution is partially based on MATILDA [7].

IV. UAV-based Industry 4.0 NetApp

To demonstrate the concept, experimental surveillance services for critical industrial infrastructures have been designed and preliminary prototyped. This NetApp performs automatic UAV-based area surveillance monitoring to detect intruders to industrial premises and provide real-time warning accordingly.

Protection against intruders is of myriad importance as the cost of commercial crimes for 7 sectors only in UK alone was about £8.6 billion in 2015/2016, and those crimes were largely intruder-related [8]. Timely surveillance can identify uninvited and potentially dangerous presence of intruders such as humans or even animals in critical Industry 4.0 infrastructure. The target of this NetApp is to help detect intruders in real time to prevent damages to be caused significantly. Empowered by advanced machine learning based human detection algorithms, and linked to efficient warning mechanisms, the NetApp services are deployed with AI surveillance algorithms running in the edge and end user monitoring devices located both locally (at infrastructure premises) and remotely. The UAV is operated at the premises and can be connected to 5G or other existing wireless networks such as WiFi.

There are mainly two ways of executing the computationally expensive algorithms for surveillance use cases using UAVs. The first is to deploy and execute the Artificial Intelligence (AI) models completely locally, e.g., in the UAV, or in the UAV controller or a smartphone connected to the controller. This localised solution avoids the transmission latency compared with the alternative approach that requires the video to be sent to the network for AI processing. Nevertheless, it is not energy efficient when allocating these AI models to the UAV/controller/smartphone processor. Furthermore, the execution speed is limited due to constrained computational powers in these portable devices, and thus real-time detection may not be feasible. In contract, in the NetApp approach, the execution of the AI models in the network side (e.g., a cloud) will benefit from the abundant computational resources such as high-spec GPUs available in the network for faster and more accurate processing whilst avoid consuming batteries of the UAV/controller/smartphone in the first approach, at a higher transmission latency though. The second approach will relieve the industry side from equipping expensive computational resources to their UAV platforms. Thus, this paper seeks to apply this NetApp in the context of 5G Induce [6], targeting to achieve real-time detection.

Fig. 3 presents the deployment of a NetApp composed of three different VNFs in this use case from the perspective of the NetApp developer, including a Video Proxy VNF, an Intruder Detection VNF, and a Publication Subscription Middleware VNF. The NAO deploys these VNFs via the NetApp Composition API and interconnects the VNFs in the 5G MEC platform. A pilot flies the UAV, which is the User Equipment (UE) in 5G terminology, on the premise.

The UE sends live video to the Video Proxy VNF, which deliver the video to the other VNFs with high performance, to mitigate the transmission latency drawback of the cloud solution. The Intruder Detection VNF employs and executes the AI-based object detection model. This is the most time-consuming task in the whole loop; nevertheless, as the processing is executed in the cloud, a high-spec GPU is deployed to achieve real-time object detection. The model provides three outputs: the coordinates of the detected object in the image, the class of the object and the probability of being that specific object. Compared with some other solutions, this VNF does not provide the detected results on the video. It just outputs the detection coordinates, thereby saving graphical overhead in the pipeline.

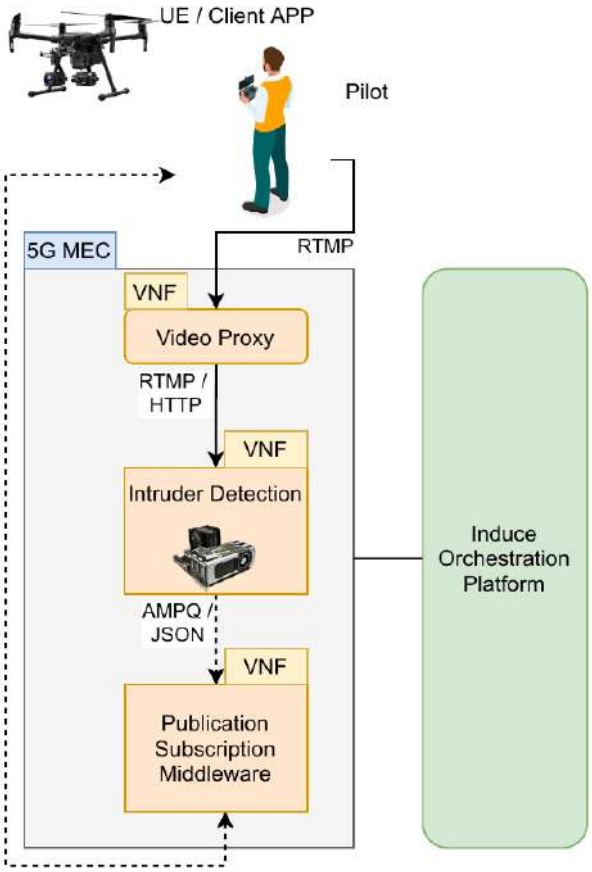

Fig. 3. VNFs deployed in 5G MEC for UAV-based intruder detection NetApp from the NetAPP developer view.

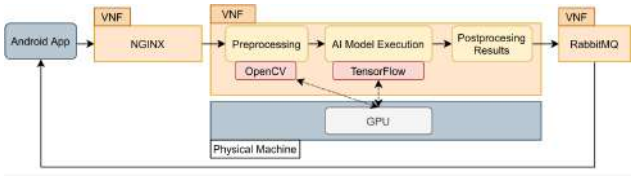

Fig. 4. Experimental Environment based on a NetApp scenario where different VNF are deployed.

The detection results are published in a Publication Subscription Middleware VNF. This VNF deploys a software that executes the common Publisher-Consumer solution, in which the UE continuously consumes the detection results while the Intruder Detection publishes the results.

V. Experimental Results

This section provides the results of the NetApp approach compared with a localised solution.

A. Experimental Environment

As shown in Fig. 4, the prototype is composed of an Android smartphone and three dockerised containers for the VNFs. While the Android App is in control of the UAV, it transmits RTMP video to a NGINX server. then the NGINX server delivers the video to the Intruder Detection VNF. The Intruder Detection NVF comprises three pipelines. First, the pre-processing pipeline carried out by OpenCV prepares the video in a proper format for the AI model. Second, the AI model implemented in TensorFlow detects the intruders on the received video. Finally, the third pipeline prepares the results in the JSON format ready to be sent to the third VNF. This last VNF employs the RabbitMQ service, which implements a AMPQ messaging protocol.

To make the VNFs to be run efficiently in the docker containers, some optimisation may be needed. In the prototype, the Intruder Detector VNF has been tuned to be fully compatible with NVIDIA graphic card, thereby taking the advantage of GPU acceleration.

The AI model implemented in this prototype is based on the YOLOv3 object recognition algorithm [9]. This Convolutional Neural Network (CNN) is computationally expensive and thus demands a high-spec GPU. Otherwise, the inference time will be significantly increased. Its detection accuracy is high, achieving 55.3 mAP [9] using the COCO dataset [10].

The experiments are performed in two scenarios: In the first scenario, which is a localised solution, the YOLOv3 is executed inside a smartphone connected to the controller via a USB cable, without being connected to a 5G network. The Android smartphone has 8GB of RAM and a Snapdragon 845 processor with a Qualcomm Adreno 630 GPU. In the second scenario,

TABLE I
STANDARD YOLOV3 MODEL TRAINED WITH TWO DIFFERENT DATASETS.

YOLOv3	Standford	UWS Dataset
Images	42462	12914
Training Set	80%	80%
Validation Set	20%	20%
Iterations	45000	15000
Accuracy	73.52%	87.94%

the NetApp for intruder detection is deployed in the 5G MEC. The GPU deployed in MEC is a GeForce GTX TITAN X NVIDIA. The UAV piloted in this scenario is a DJI Inspire v1 drone, which streams live video at a resolution of 1280x720 pixels and 24 frames per second (FPS).

B. Quantitative Results

For quantitative results, YOLOv3 was trained with two datasets (tab. I). First, the training was conducted over a public dataset named Stanford Drone Dataset (SDD) for human detection from UAV [11]. This will allow other researchers to compare their work with these results. Moreover, we trained YOLOv3 with a private UWS dataset allowing us to perform intruder detection in industrial areas [12] and wildness for smart agriculture scenarios. Thousands of frames were extracted and manually labelled to provide the ground truth for the training process. The training process was executed offline. Thanks to the additional training dataset, the detection accuracy has been significantly improved from 73.52% to 87.94%, as shown Table I.

We have compared the two approaches: a localised solution based on the smartphone [13], [14] and the NetApp solution. Table II presents the comparison results in terms of model size, loading time, and inference time of the employed scenarios. Although the same AI model and same weights are used, the size is different depending on the execution environment. In the smartphone solution, the model is transformed into the Snapdragon Neural Processing Engine (SNPE) format to exploit the full capabilities of the Snapdragon GPU. In contrast, the NetApp executes the neural network in TensorFlow. The SNPE is more efficient as it compresses the neural network by 24MB. Regarding the loading time to the GPU, the TensorFlow deployment in the NetApp takes 422ms more to load compared with the Snapdragon. It is noted that the loading time only occurs once at the beginning of the process. Therefore, it is not a determining metric. In contrast, the inference time is a process continuously performed every time a video frame is received for detection. This metric is the time taken since the frame is received by the CNN until the results are presented. Here, there is a decisive difference between the two approaches: 594 ms when in the smartphone solution, compared with the impressive 37 ms achieved in the NetAPP solution.

TABLE II
MODEL SIZE, LOADING TIME AND INFERENCE TIME OF EMPLOYED SCENARIOS.

	Model Size	Loading Time	Inf. Time
Smartphone	224 MB	2618 ms	594 ms
NetApp	248 MB	3040 ms	37 ms

These results clearly favour the NetApp solution. Meanwhile, we need to consider the transmission latency of the video sent over the network. Fig. 5 shows the cumulative average of frames and the amount of time taken until the detection results are presented. For the smartphone solution, we just need to consider the inference time as no transmission latency is caused. The NetApp needs to consider the latency sum of the inference time and the video transmission latency.

However, the smartphone is only able to detect 1.68 FPS and thus discards the other 22.32 FPS out of the 24 FPS streamed. Consequently, the smartphone solution led to the delay of 594 ms. The NetApp solution is able to detect each frame of the video at 24 FPS, providing the results with a delay of 368 ms. This in turn has a great impact on the accuracy of the NetApp solution since it is capable of detecting 22 more frames than the smartphone solution is. Overall, the NetApp solution outperforms the smartphone solution significantly, and thus we have validated our proof of concept for the NetApp approach.

C. Qualitative Results

In Fig. 6, some screenshots were taken for the NetApp solution, as shown in Fig. 6(a) for the detection of two intruders in an industrial site. The UAV was flying at 15 meters of altitude. Figures 6(b) and 6(c) further illustrate a smart agriculture scenario where the UAV was flying at 25 meters and the intruder was hiding in

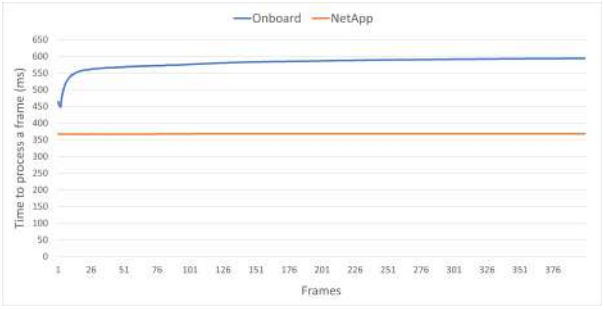

Fig. 5. Accumulate average of the amount of time taken to process a video in both scenarios.

tall grass. As seen in the figures, the detection results were all successful, and the delay was negligible.

VI. Conclusions

This paper has provided a novel view in splitting an application into distributed Virtual Network Functions to achieve a NetApp approach for vertical businesses to benefit from 5G services. These NetApps provide to the industry sectors a new way to enable their applications in 5G networks, achieving advanced performance by leveraging powerful edge computing capabilities among others. In addition, the NAO and its integration with the OSS extends the capabilities allowing an easy interfacing with the vertical end users and application developers. We have demonstrated how the deployment of a UAV's intruder detector in a NetApp scenario reduces the delay of detection in 226 ms (38%). Moreover, this solution is able to perform object detection in every frame in contrast to the localised solution where it is just able to detect at 1.68 FPS.

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References

[1] K. Trichias *et al.*, "Vital-5g: Innovative network applications (netapps) support over 5g connectivity for the transport amp; logistics vertical," in *EuCNC/6G Summit*, pp. 437–442, 2021.

[2] K. C. Apostolakis *et al.*, "Cloud-native 5g infrastructure and network applications (netapps) for public protection and disaster relief: The 5g-epicentre project," in *EuCNC/6G Summit*, pp. 235–240, 2021.

[3] Smart5GGrid, "Smart5grid: Demonstration of 5g solutions for smart energy grids of the future," 8 Oct 2021.

[4] 5G-ERA, "5g enhanced robot autonomy," 8 Oct 2021.

[5] 5G-IANA, "5g intelligent automotive network applications," 8 Oct 2021.

[6] 5G-INDUCE, "Open cooperative 5g experimentation platforms for the industrial sector netapps."

[7] P. Gouvas *et al.*, "Separation of concerns among application and network services orchestration in a 5g ecosystem," in *EuCNC*, 2018.

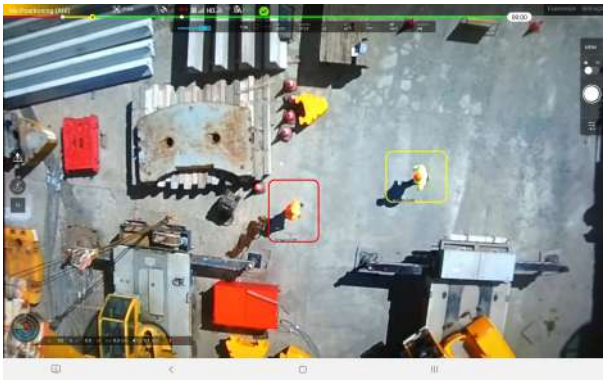
[8] M. Heeks, S. Reed, M. Tafsiri, and S. Prince, "The economic and social cost of crime," 8 Oct 2021.

[9] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," 2018.

[10] T.-Y. Lin *et al.*, "Microsoft coco: Common objects in context," in *ECCV*, 2014.

[11] G. Golcarenarenji, I. Martinez-Alpiste, Q. Wang, and J. Alcaraz Calero, "Efficient real-time human detection using unmanned aerial vehicles optical imagery," *International Journal of Remote Sensing*, vol. 42, pp. 2440–2462, 04 2021.

[12] G. Golcarenarenji, I. Martinez-Alpiste, Q. Wang, and J. Alcaraz Calero, "Machine-learning-based top-view safety monitoring of ground workforce on complex industrial sites," *Neural Computing and Applications*, pp. 1–15, Aug. 2021.



(a) "Intruders" at an industrial site.

(b) "Intruder" in the wild.

(c) "Intruders" hiding in the wilderness.

Fig. 6. Screenshots taken from the smartphone while receiving the detections from the NetApp.

[13] I. Martinez-Alpiste, G. Golcarenarenji, Q. Wang, and J. Alcaraz Calero, "Smartphone-based real-time object recognition architecture for portable and constrained systems," *Journal of Real-Time Image Processing*, 09 2021.

[14] I. Martinez-Alpiste, P. Casaseca-de-la Higuera, J. Alcaraz-Calero, C. Grecos, and Q. Wang, "Smartphone-based object recognition with embedded machine learning intelligence for unmanned aerial vehicles," *Journal of Field Robotics*, vol. 37, 11 2019.