Abstract— Pilgrimage represents the most important Islamic religious gathering in the world where millions of pilgrims visit the holy places of Makkah and Madinah to perform their rituals. The safety and security of pilgrims is the highest priority for the authorities. In Makkah, 5000 cameras are spread around the holy for monitoring pilgrims, but it is almost impossible to track all events by humans considering the huge number of images collected every second. To address this issue, we propose to use artificial intelligence technique based on deep learning and convolution neural networks to detect and identify Pilgrims and their features. For this purpose, we built a comprehensive dataset for the detection of pilgrims and their genders. Then, we develop two convolutional neural networks based on YOLOv3 and Faster-RCNN for the detection of Pilgrims. Experiments results show that Faster RCNN with Inception v2 feature extractor provides the best mean average precision over all classes of 51%. 

Index Terms— Pilgrim Detection, Convolutional Neural Networks, Deep Learning, You Only Look Once (Yolo), Faster R-CNN.

I. INTRODUCTION

Artificial Intelligence (AI) represents nowadays the hottest technology ever with a huge impact of the societies and services provided in different types of applications. One the main driving factors of artificial intelligence in the last decade is the emergence of deep learning in computer vision applications and more particularly with convolutional neural networks (CNNs). In fact, with the emergence of AlexNet [1] in 2012, the computer vision community aggressively moved to the application of CNN for image classification, detection, recognition and semantic segmentation. Deep learning approaches have been used in a variety of use cases namely people behavior monitoring [2], vehicles detection [3], [4], semantic segmentation of urban environments [5], self-driving vehicles [6], object detection and classification [7], [8], semantic segmentation [9], [10], [11].

In this paper, we address the problem of developing AI-based solutions for pilgrims detection and monitoring in Hajj and Umrah events, in Saudi Arabia. In fact, Hajj and Umrah attract annually millions of pilgrims from all over the world. According to Ministry of Hajj, the number of Umrah Visas issued in 2019 is around 7.5 millions and the number of pilgrims during the 5 days of the annual Pilgrimage reached 2.5 millions. The Vision 2030 of the Kingdom of Saudi Arabia aims to attract annually millions of pilgrims from all over the world. To solve this problem, we use the YOLOv3, which is orders of magnitude faster and has low complexity. Faster R-CNN led to a tracking rate of 92.51% on the simple standard dataset and 76.9% on the RGB-D People dataset. The algorithm led to a tracking rate of 92.51% on the simple standard dataset and 76.9% on the RGB-D People dataset.

Wang et al.[15] were interested in the problems of the pedestrian detection and tracking failure caused by the commonly used methods of tracking. To solve this problem, for the detection, they used the Faster-RCNN framework, and for the monitoring, they used the Person-ReID method based on feature extraction and matching between different frames. This algorithm led to a tracking rate of 92.51% on the simple standard dataset and 76.9% on the RGB-D People dataset.

II. RELATED WORKS

Several recent works have used CNN for people’s behavior monitoring, but there were applied to contexts different from Pilgrims detection.

In this paper, the contribution are three-folded. First, we build a large dataset of pilgrim and non-pilgrim instances for different genders and in different environment. Second, we have train two state-of-the-art CNN algorithms for the specific use case of pilgrim detection, namely YOLOv3 [12] and Faster R-CNN. YOLOv3 is known as begin the fastest detection algorithm, whereas Faster R-CNN [13] is an improvement of R-CNN [14] that represents the most efficient region-based CNN algorithm for image detection. Third, we conduct a comparative study between these two algorithms to evaluate their performance in the context of pilgrimage detection.

The remainder of the paper is organized as follows. Section II discusses related works on deep learning for people monitoring and existing non-AI techniques for pilgrim monitoring. Section III presents a brief background on both state of the art CNN algorithms, namely YOLOv3 and Faster R-CNN. Section IV presents details on the Pilgrim dataset that we built for this study. Section V presents and discussed the main results. Section VI concludes the paper and outlines future works.
of detection, we used Faster R-CNN, with two different features extractor (Inception-v2 and ResNet50) that give us the best feature map that helps us to do the detection task.

On the other hand, several techniques [17], [18] were applied for pilgrims detections using sensing and mobile technologies, but not using deep learning methods.

Teduh et al.[17] proposed an architecture of geo-fencing emergency alerts system for Hajj pilgrim. The proposed architecture is based on mobile phones with GPS module, which is used as pilgrims’ tracking devices. It is also created to handle the predicted load using a specific algorithm.

Mohandes et al.[18] developed a prototype of a wireless sensor network for tracking pilgrims in the Holy areas during Hajj. They used a principle delay tolerant network. In this system, a network of fixed master units is installed in the Holy area. Besides, every pilgrim will be given a mobile sensor unit that includes a GPS unit, a Microcontroller, antennas, and a battery that aims to sends its UID number, latitude, longitude, and time.

These works that were applied for pilgrims’ detections using sensing and mobile technologies also present several problems such as, (i.) The difficulty to receive the GPS signal in some area cause problem for the pilgrim tracking system using GPS. (ii.) The difficulty of working this system in a large crowd because it can’t use big data.

To solve these problems, we propose to use a computer vision deep learning for pilgrim detection in real-time. Also, it can be easily integrated to monitor pilgrims using the CCTV camera infrastructure in holy mosque areas.

III. ALGORITHMS BACKGROUND

For the pilgrims’ detection, we are using the Faster R-CNN [13] and YOLOv3[12] algorithm. In this section, we present the different versions of these algorithms and the difference between them.

A. Faster R-CNN

In this section, we provide an overview of the Faster R-CNN [13] algorithm for the detection of pilgrims. It is an improved version of R-CNN [14], which has been conceived to bypass the problem of selecting a huge number of regions. This problem is inherent to the use of the conventional CNN algorithm for object detection.

• The region proposal network RPN

• A Fast R-CNN detector

The Fast R-CNN detector is composed of the two following steps:

- The extraction of features vectors from the region of interest ROIs using the ROI pooling.
- The feature vector obtained is the input of the classifier composed of fully connected layers.

The classification step output is:

- A sequence of probabilities estimated of the different object considered
- The coordinates of the regions proposals

B. YOLOv3

YOLO or You Only Look Once is an improved version of convolutional neural network CNN, which is used especially for object detection, because the CNN, as originally conceived, is very time-consuming. There are three versions of YOLO. YOLOv3 [12], which is an improved version of YOLOv2 [19] and YOLOv1 [20]. It is characterized by:

- The use of multi-label classification based on logistic regression instead of the Softmax function.
- The use of cross-entropy loss function instead of the mean square error for the classification loss.
- The prediction of different bounding boxes based on the overlapping of the bounding box anchor with the ground truth object.
- The use of the concept of Feature Pyramid Network for the prediction by predicting boxes at three different scales and then extracting features from these scales. And the result of the prediction is a 3D tensor encoding the bounding box, the objectness score, and the prediction over classes.
- The use of Darknet-53 CNN features extractor, which is composed of 53 convolutional layers Instead of Darknet-19, using 3x3 and 1x1 filters and the skip the connection network inspired by ResNet [21].

IV. THE PILGRIMS DATASET

In this paper, we are interested in building a comprehensive dataset for the detection of pilgrims and their genders.

For the woman, we cannot differentiate the pilgrims from the not pilgrims because their clothes are so similar. For this purpose, we choose to put the pilgrim and not pilgrim woman in the same class.

Contrariwise, the pilgrim man has specific clothes that are as different from other clothes, as we can see in Figure 3.a. For this, we choose to divide the man class into pilgrim and not-pilgrim. For the not-pilgrim class, we are focused on the white Saudi clothes, as we can see in Figure 3.b because they are quite identical, especially in term of color.

To create our dataset, we collected 622 images of a person in the holy places of Makkah and Madinah. We choose images of persons in different environments and situations, and these images are taken from different sides and illumination. Then, using the LabelImg software [22], we labeled the collected dataset into three labels chosen, namely woman, pilgrim, and not-pilgrim. We obtained a dataset composed of 1165 women and 2291 man instances, which is divided into 1339 pilgrim and 952 not-pilgrim instances. The statistics of dataset instances are presented in table I.

Our dataset is a Pascal VOC [23] (Pascal object classes) dataset composed of 3 classes (woman, pilgrim, not pilgrim).
We choose the Pascal VOC dataset because it enables evaluating our proposed YOLOv3 and Faster R-CNN pilgrim detection algorithm in significant variability in terms of object size, orientation, pose, illumination, position, and occlusion [23].

V. EXPERIMENTAL EVALUATION

In this section, we describe the results of the experimental study that we conducted to evaluate the performance of the pilgrim detection use case using two state-of-the-art algorithms, namely YOLOv3 and Faster R-CNN. We start by describing the experimental setup, and we present the metrics used for the evaluation of the proposed algorithm. Finally, we analyze the results obtained for each algorithm to compare their performances

A. Experimental Setup

In this experimental study, the training was done on two machines. The configurations of these two machines are presented in Table II.

| CPU                  | Graphics card | RAM     | Operating system |
|----------------------|---------------|---------|------------------|
| Machine 1            | Machine 2     |         |                  |
| Intel Core i7-8700K  | NVIDIA        | 32GB    | Linux (Ubuntu 16.04 TLS) |
| (3.7 GHz)            | GeForce 1080  |         |                  |
| (8 GB) GPU           | NVIDIA        |         |                  |
| Intel Core i9-9900K  | GeForce RTx2080T |     |                  |
| (Octa-core)          | (11 GB) Gaming Cpu |     |                  |

We chose to use three different input sizes that have values of (320x320, 416x416, and 608x608). These settings result in five classifiers trained and tested on our pilgrim dataset. The training of these two algorithms is made to detect and recognize three classes of persons that are (Woman, Pilgrim, and Not-Pilgrim). To optimize these two algorithms, we used Stochastic Gradient Descent (SGD) with a default value of momentum (0.9). For the learning rate, we used an initial rate of 0.001 for YOLOv3, and for the Faster R-CNN, we used an initial rate of 0.0002 with Inception-v2 and 0.0003 with ResNet50, which are the default value of each feature extractor network. We used the weight decay value of 0.0005.

B. Performance evaluation and metrics

For the evaluation of our proposed algorithms, we have used six metrics based on the following parameters:

- True Positive (TP): it is the number of instances (woman, pilgrim, and not-pilgrim) successfully detected and classified.
- False Positive (FP): it refers to the number of instances that are wrongly classified.
- False Negative (FN): It is the number of non-detected instances.

The six metrics used for the evaluation are:

- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1Score = 2 * Precision * Recall / (Precision + Recall)
- Quality = TP / (TP + FP + FN)
- mIoU: mean of the Intersection over Union that measures the overlap between the predicted and the ground-truth bounding boxes.
- mAP: mean Average Precision. Or AP (Average Precision) when it is measured on one class. It is an approximation of the area under the precision-recall curve [4].
- FPS: frame per second. It presents the inference speed of the algorithm.

C. Comparison between Faster R-CNN and YOLO v3

For the evaluation of the proposed algorithms, we compared the values of the six metrics for each algorithm shown in Table III and Table IV.

1) FN, TP and FP: Figure 3 shows that when we used the YOLOv3, the number of false negatives is much higher than the number of false positives on over classes, and also much higher than the number of true positives, which indicates that most instances go undetected. And when using the Faster R-CNN, the number of true positives is much higher than the number of false positives and the number of false negatives on over classes, which indicates that most instances go detected.

2) Average Precision: When analyzing the results, it appears that YOLOv3, with an input size of 608x608, gave a better mAP for the Pilgrim Class and Faster R-CNN with Inception-v2 gave a better mAP on Non-Pilgrim Class (Figure 4). Figure 4 shows also that Faster R-CNN with Inception-v2 gave a much better mAP over classes.

3) Precision and mIoU: The results of Average IoU, show that YOLOv3 gave a better IoU over classes than Faster R-CNN. And the results of precision show that YOLOv3, with an input size of 320x320, gave a much better precision on Pilgrim Class. It also shows that YOLOv3, with an input size of 320x320, gave a much better precision over classes with a ratio of 80.58%.
4) Recall: Analyzing the average recall results, we found that Faster R-CNN outperforms YOLOv3 in this metric with a slightly better performance with the ratio of 59.29% for Inception-v2 feature extractor over ResNet50, and a marked inferior performance for YOLOv3 with an input size of 320x320.

5) Robustness: When analyzing the quality that measures the robustness of the algorithms, it appears that YOLOv3 gave a better quality for the Non-Pilgrim Class, and Faster R-CNN gave a better Precision on Pilgrim Class. It also seems that Faster R-CNN with Inception-v2 gave a much better precision over classes with a ratio of 41.72%.

The F1score that also measures the robustness based on the precision and the recall ratios reveals that YOLOv3, with an input size of 608x608, gave a better performance with a ratio of 66.01% for the Pilgrim Class and Faster R-CNN gave a better precision also on Pilgrim Class with a ratio of 59.45%. And over all classes, Faster R-CNN with Inception-v2 gave a much better score with a ratio of 58.87%.

6) Inference Processing time: The results of the average Inference speed measured in Frames per Second (FPS), for each of the tested algorithms, show that YOLOv3 is 19 times faster than Faster R-CNN in the inference phase.

7) Effect of the feature extractor: When analyzing the effect of the feature extractor for Faster R-CNN, it appears that Resnet50 feature extractor is slightly faster than Inception-v2 because it is less computationally complex. But, Inception-v2 outperforms ResNet50 on almost all metrics.

8) Effect of the input size: Table IV shows a significant gain in YOLOv3's AP when moving from a 320x320 input size to 608x608. But it shows a substantial loss in YOLOv3's precision when moving from a 320x320 input size to 608x608. That also indicates that the input size has an important impact on the inference processing speed of YOLOv3 because a larger input size generates a higher number of network parameters and operations (FPS from 43 FPS for 608*608 up to 91 FPS for 320*320).

In this section, we compared the performance of YOLOv3 (with three different input sizes) and Faster R-CNN (with two different feature extractors) and the impact of the input size and the features extractor. Figure 5 summarizes the main results.
VI. CONCLUSIONS

In this paper, we developed convolutional neural network models for pilgrim detection for AlHajj based on YOLOv3 and Faster RCNN. We have built a dataset containing three classes of a pilgrim, non-pilgrim and women. Experimental results show that Faster RCNN with Inception v2 feature extractor provides the best mean average precision over all classes of 51%. In our future work, we will extend the dataset to have several tens of thousands of instances to improve the overall accuracy and precision, and we will consider more classes. We also aim at developing a search application for lost people during Hajj and Umrah based on some predefined features.

APPENDIX

Appendixes should appear before the acknowledgment.

ACKNOWLEDGMENT

This work is supported by the Robotics and Internet-of-Things Lab of Prince Sultan University.

REFERENCES

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, pp. 1097–1105, 2012.
[2] A. Koubaa, A. Ammar, A. A.-H. Bilel Benjdira, B. Kawaf, A. B. Saleh Ali Al-Yahri, K. Assaf, and M. B. Ras, “Activity Monitoring of Islamic Prayer (Salat) Postures using Deep Learning,” arXiv pre-print 1911.xxxxx, November 2019.
[3] B. Benjdira, T. Khursheed, A. Koubaa, A. Ammar, and K. Ouni, “Car Detection using Unmanned Aerial Vehicles: Comparison between Faster R-CNN and YOLOv3,” in 2019 1st International Conference on Unmanned Vehicle Systems-Oman (UVS), pp. 1–6, IEEE, 2019.
[4] A. Ammar, A. Koubaa, M. Ahmed, and A. Saad, “Aerial Images Processing for Car Detection using Convolutional Neural Networks: Comparison between Faster R-CNN and YoloV3,” arXiv pre-print 1910.07234, October 2019.
[5] B. Benjdira, Y. Bazi, A. Koubaa, and K. Ouni, “Unsupervised Domain Adaptation Using Generative Adversarial Networks for Semantic Segmentation of Aerial Images,” Remote Sensing, vol. 11, no. 11, 2019.
[6] B. Schoettle and M. Sivak, “A survey of public opinion about autonomous and self-driving vehicles in the us, the uk, and australia,” tech. rep., University of Michigan, Ann Arbor, Transportation Research Institute, 2014.
[7] I. Ševo and A. Avramović, “Convolutional Neural Network Based Automatic Object Detection on Aerial Images,” IEEE Geoscience and Remote Sensing Letters, vol. 13, pp. 740–744, May 2016.
[8] K. S. Ochoa and Z. Guo, “A Framework for the Management of Agricultural Resources with Automated Aerial Imagery Detection,” Computers and Electronics in Agriculture, vol. 162, pp. 53 – 69, 2019.
[9] M. Kampffmeyer, A. Salberg, and R. Jenssen, “Semantic Segmentation of Small Objects and Modeling of Uncertainty in Urban Remote Sensing Images Using Deep Convolutional Neural Networks,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 680–688, June 2016.
[10] S. M. Azimi, P. Fischer, M. Körner, and P. Reinartz, “Aerial LaneNet: Lane-Marking Semantic Segmentation in Aerial Imagery Using Wavelet-Enhanced Cost-Sensitive Symmetric Fully Convolutional Neural Networks,” IEEE Transactions on Geoscience and Remote Sensing, vol. 57, pp. 2920–2938, May 2019.

[11] L. Mou and X. X. Zhu, “Vehicle Instance Segmentation From Aerial Image and Video Using a Multitask Learning Residual Fully Convolutional Network,” IEEE Transactions on Geoscience and Remote Sensing, vol. 56, pp. 6609–6711, Nov 2018.

[12] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” CoRR, vol. abs/1804.02767, 2018.

[13] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with,” IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, 2017.

[14] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 580–587, 2014.

[15] C. Wang, X. Sun, and H. Li, “Research on pedestrian tracking algorithm based on deep learning framework,” in Journal of Physics: Conference Series, vol. 1176, p. 032028, IOP Publishing, 2019.

[16] V. Molchanov, B. Vishnyakov, V. Vizilter, O. Vishnyakova, and V. Knayaz, “Pedestrian detection in video surveillance using fully convolutional yolo neural network,” in Automated Visual Inspection and Machine Vision II, vol. 10334, p. 103340Q, International Society for Optics and Photonics, 2017.

[17] T. Dirgahayu and S. Hidayat, “An architectural design of geofencing emergency alerts system for hajj pilgrims,” in 2018 8th International Conference on Computer Science and Information Technology (CSIT), pp. 1–6, IEEE, 2018.

[18] M. Mohandes, M. A. Haleem, A. Abut-Hussain, and K. Balakrishnan, “Pilgrims tracking using wireless sensor network,” in 2011 IEEE Workshops of International Conference on Advanced Information Networking and Applications, pp. 325–328, IEEE, 2011.

[19] J. Redmon and A. Farhadi, “Yolo9000: better, faster, stronger,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7263–7271, 2017.

[20] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pp. 779–788, 2016.

[21] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” Arxiv.Org, 2015.

[22] D. Tzutalin, “Labelimg. git code (2015). https://github.com/tzutalin/labelimg.”

[23] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (voc) challenge,” International journal of computer vision, vol. 88, no. 2, pp. 303–338, 2010.

[24] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.

[25] J. Huang, V. Rathod, C. Sun, M. Zhu, A. Korattikara, A. Fathi, I. Fischer, Z. Wojna, Y. Song, S. Guadarrama, et al., “Speed/accuracy trade-offs for modern convolutional object detectors,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 7310–7311, 2017.