R. ESTRADA, Y. DELAHOZ, G. JOHSON, M. LABRADOR. A water-on-floor detection system for the elderly and the visually impaired. Gerontechnology 2018;17(Suppl):93s; https://doi.org/10.4017/gt.2018.17.s.091.00
Purpose The World Health Organization (WHO) reported in September 2016 that falls are the second leading cause of accidental deaths in the world[1]. There are an estimated 424,000 fatal falls every year and another 37.3 million non-fatal falls requiring medical attention with elderly people being the highest at risk group[2]. An important fall hazard is the presence of puddles or wet floors. While several studies have proposed different approaches to fall prevention, most of them focus on floor and/or object detection. Detection of bodies of water has only been researched in the context of identifying bodies of water from satellite images, or outdoor water hazards for autonomous navigation. Therefore, detecting indoor puddles is an area that has not been probed and could help elderly people and those with visual impairments avoid slipping, falling, and potentially injuring themselves. **Method** This work proposes a water detection system based on deep neural networks trained to identify bodies of water from single daytime images taken from a sequence of video frames filmed with a smartphone's camera. Since no public dataset regarding indoor water detection is available, 46 videos with 1920x1080 resolution were taken using a Pixel G-2PW4100 5" 32GB. 4060 single frames were extracted from these videos using ffmpeg with 4 frames/second. These frames were labeled manually to mark those pixels (black) that belong to a water area in the image. *Figure 1* shows an example of this procedure. Data augmentation is applied to the captured frames to create a bigger dataset. The images were cropped into 9 separate images, resized to 500x500, and then superpixels were created to paint the water puddles. The data augmentation process produced 36,540 images that would consist of our entire dataset for this project. These images were split into a training, validation, and testing dataset, with the split being 70/5/25 respectively. Different types of deep convolutional neural networks with varying parameters were created and trained to look for the best possible results. *Figure 2* shows an example of one network topology. After the construction of the different network topologies, they are trained and evaluated. TensorFlow[3] and OpenCV[4] are used to perform these tasks. **Results & Discussion** Once the model was trained, it was evaluated against the test dataset so that the data used was not part of the training process and to determine how the model will perform in new indoor environments. The evaluation module worked with a batch size of 50 and the metrics computed were accuracy, precision and recall. Accuracy measures the number of correct classifications of both water and non-water areas. Precision measures the correct classification of water areas over all the areas the net classified as water. Recall measures the correct classification of water areas over all the areas that were in fact water. The best network topology achieved a 92.67% of accuracy, 19.33% of precision and 73% of recall.

References

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Address: University of South Florida;
E: raulestradab@mail.usf.edu

Figure 1. Image Labeling

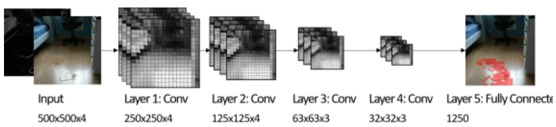

Figure 2. Network Topology