Food:

Advances in the field of sensor devices to monitor the quality of food has grown extensively over the last few decades. Existing food and liquid sensing techniques are either too costly and bulky, such as spectroscopes, or are invasive and inaccurate, such as RF-based sensing. Conventional RFIDs are not extendable to different environments, as the RFID signal is highly sensitive to near and far-field coupling, which depends on content and the surrounding environment. The RFID reader is usually calibrated to perform under different environments and with different content. RF-EATS senses food and liquids non-invasively and requires no calibration. The design is compatible with existing RFID tags. The reader relies on a novel learning framework that makes sensing generalizable to unseen environments with an average accuracy of 90% across different samples and environments. However, the design is incapable of resolving small dielectric differences between the content materials.

Design:

At its core, RF-EATS employs a neural learning model that learns the RF features due to the sample regardless of the environmental changes. However, the neural learning models require very large datasets, which is costly and time consuming, while still not being fully capable of generalizing to unseen environments. Thus, RF EAT readers use variational auto encoder (VAE) to produce a large number of realistic synthetic data from a small number of real-world measurements.

The VAE uses a multi-path kernel function that dissects the measured wireless channel to content and environment-dependent features. This classification is important to train the generative model. The environment-dependent features capture practical radio environments. The VAE uses latent variables to cover a broad-spectrum of possible environmental setups. Since the VAE is trained to minimize reconstruction loss, if the inputs to the VAE encode environment-dependent features and the reconstruction loss goes up, anomalies in the contents can be detected.

Once a well-trained model is generated, the real synthetic data output from the VAE is fed to a feature encoder that generates features for use in classification. The feature encoder consists of common and task-specific layers. The output features are fed to the Classifier to yield the classification results. Propagation-related features can be re-used across different environments, and hence generalize to unseen environments. However, retraining needs to be done for different tasks (i.e. different content sensing).

Implementation and Evaluation:

The design is implemented on USRP X310 and N210 software radios. The radios use EPC-Gen2 protocol and transmit high power frequency to power up the device, and a low power sensing frequency within 500-1000 MHz. At the receiver, a low pass filter is used to attenuate the interference from the power up signal, and an LNA is used to boost the sensing signal. The processing is done offline using MATLAB and python software. The receiver performs standard channel estimation using the packet preamble. The transfer learning classifier uses Adam optimizer with *learning rate*=$1e^{-4}$, *beta1 = 0.9, beta2 = 0.999, dropout rate = 0.2*. The VAE encoder and decoder consist of 3 hidden layers each. The dimension of latent variable was set to 16. The Adam optimizer was set up with *learning rate*=$1e^{-7}$, *beta1 = 0.9, beta2 = 0.999, dropout rate = 0.2*. Off-the-shelf passive UHF RFIDs, particularly the Alien ALN-9640 Squiggle and Smartrac tags were used.

RF-EATS was tested in 7 different applications with 2,048 samples in total and in 20 different environments but all in practical real-life scenarios. The RFID reader was placed within 10-20 cm distance at $\pm$ 45 degrees orientation. When trained and tested in the same environment, RF-EATS achieves an accuracy greater than 90% for different applications. The minimum accuracy drops to 83% when testing is done in new unseen environments, with a median improvement of 15.1% over simple neural networks, 26.5% over RFIQ and 29% over ray-tracing model over all applications. However, the performance of RF-EATS depends heavily on the dielectric differences between contents of interest. The 90% accuracy is achieved when the dielectric difference is over 200 and drops to 77% at the lowest difference of 15.

Discussion:

During the class discussion, students acknowledged the novelty of the neural learning concept and credited the authors for following through with a complete prototype implementation. The transfer learning model in particular appealed to the class as it significantly made RF-EATS a lot more user friendly than existing work by reducing the time needed for training. However, several students hoped for a more detailed study of the performance metrics of the machine learning model, such as the variations of the latent variables across different experiments and the impact of container material and shape as well. Several students also criticized the significant dielectric difference between the contents used while conducting the different experiments. The accuracy should have been reported for finer differences between the content materials. The accuracy enhancement due to increased BW was not quite clear to several students and required further elaboration.