Image Transmission using LoRa for Edge Learning

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***Abstract*—With the advent of edge computing, sensor data is increasingly collected, processed, and actioned at the network edge. Especially, the sensor data that comes in the form of images are greatly benefited by the machine learning capabilities of edge computers, which reduce the traffic to cloud servers and the network latency. When it comes to sensor networks that transport these data, LoRa communication provides low cost, low power, and long-range communication for a multitude of applications. However, image transmission using LoRa has always been challenging due to the low data rates, high transmission time, and duty cycle limitations. The machine learning algorithms, however, have demonstrated promising performance with minimal image quality. Hence, this paper analyses the performance of edge learning with sensor images transmitted through LoRa networks. Such systems will find applications in wildlife monitoring, crop and farm monitoring, pest control, and marine observation where long battery life and long range communication is warranted. The proposed system finds the optimal image compression so that the transmission time is minimum while ensuring the detection at the edge. Our hardware implementation demonstrates that the transmission time could be brought to below 20 seconds, which is around 90% drop from the original quality images and is compliant with LoRaWAN duty cycle limitations.**

Keywords*—*LoRa, LoRaWAN, Edge Computing, Edge Learning

I. Introduction

Nowadays, sensor networks are a popular topic of interest due to the introduction of Internet of Things (IoT). A wide variety of technologies are used to build sensor networks such as Wi-Fi, 5G cellular communication, ZigBee, NB-IoT, and LoRa/LoRaWAN [1], [2]. These technologies have their own characteristics that decide the range, data rate, reliability and cost when used in sensor networks. For instance, Wi-Fi is suitable for indoor sensor networks and is capable of supporting high data rates, while 5G cellular networks are useful for outdoor long range networks at a considerably higher cost.

Among these candidate networks, LoRa networks are being widely deployed due to their long range, low capital and operational cost, and low power consumption [2]. Typically, LoRa devices can transmit up to 5 km in urban areas and reach more than 15 km in rural areas. Further, the battery life can be up to 10 years if the sensors nodes are designed properly [3]. Invented by Semtech, LoRa physical layer is based on a proprietary spread-spectrum technique. However, a wide area networking (WAN) protocol stack called LoRaWAN is developed by the LoRa Alliance based on LoRa for global operation of LoRa devices [4].

Combined with the edge computing facilities that are deployed at the network edge, LoRa-based sensor networks are now capable of analyzing the plethora of data thrown at them [5]. However, LoRa networks are at a disadvantaged position when it comes to image-based sensor data due to their low data rate. Usually, image transmission with LoRa networks take a few minutes for completion and the LoRaWAN specifications do not allow such long transmissions to comply with government regulations on spectrum usage [6]. Therefore, sensor networks that transmit images are reluctant to use LoRa as the communication link. Despite that, if the images are used by machine learning algorithms at the network edge, there is a possibility of reducing the image quality as most machine learning algorithms work quite well even with low image quality [7]. Therefore, if the images are downscaled properly, LoRa networks should be able to transmit them within regulated timescales for the learning algorithms to process at the network edge.

In light of these developments, this paper proposes a system that can transmit images for edge learning using LoRa communication networks. The diagram shown in Fig. 1 gives an overall idea of the proposed system. The LoRa-enabled sensor nodes are deployed in remote locations such as wildlife parks, farms, coastal areas and the LoRa gateway maintain the connectivity with them. The images are transmitted through LoRa links and are sent to the edge computer from the LoRa gateway. The paper analyses the transmission time for different image quality levels and checks whether the learning algorithms work well with the varying image quality.

The rest of the paper is organized as follows. The Section II discusses the existing work in this area and their strengths and shortcomings. The Section III presents the proposed architecture and hardware implementation in detail. The conducted experiments and their results are presented in Section IV. Finally, the Section V concludes the paper.

II. Related Work

There have been a number of studies on transmitting images via LoRa communication. Some of them aim to execute machine learning algorithms on the received images. One of the earliest attempts to transfer images over a LoRa network was presented in [8]. The authors have implemented a packet loss tolerant image compression technique that can run on limited memory platforms. Their hardware implementation was based on Teensy3.2 board as the host micro controller to drive the CMOS uCamII camera. They retrieve raw 128×128 8 bits per pixel (8-bpp) grey scale images from the camera and then operated image compression on the board. They have used an optimized encoding scheme and the compression scheme was a JPEG-like coder and operated on 8×8 pixel blocks with advanced optimizations on data computation to keep the computational overhead low. The combination of the fast JPEG-like encoder with an optimized block interleaving method has allowed them an efficient tuning between the compression ratio and energy consumption trade-off while maintaining an acceptable visual quality in case of packet loss. However, the surveillance part

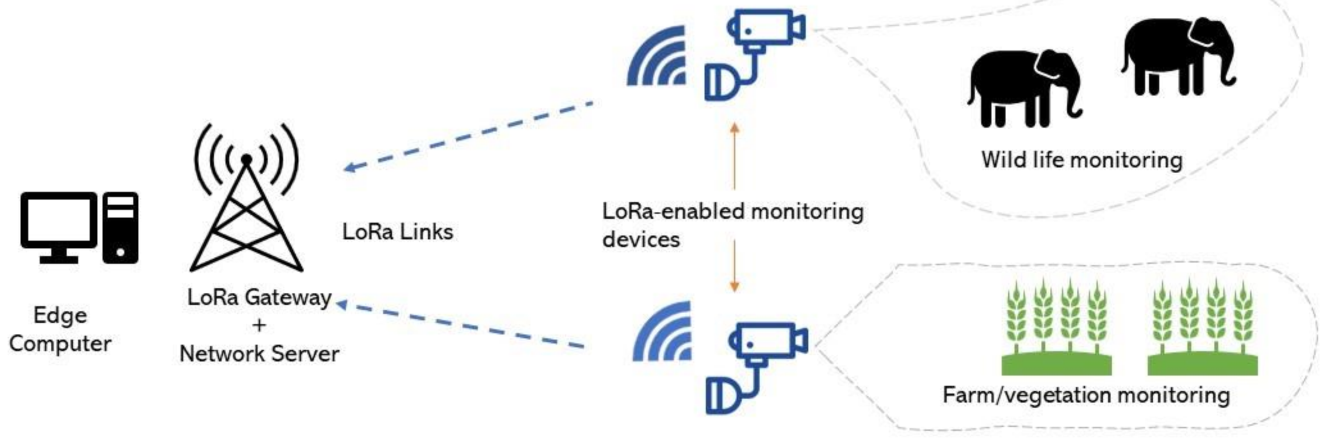


Fig. 1: System Overview.

of the work in broadly manual without an involvement of any artificial intelligence.

The Multi-Packet LoRa (MPLR) protocol proposed in [6] is a lightweight and reliable protocol which can transmit images (or other large files) as batches of multiple packets. This protocol uses bit-vector acknowledgement packets that give the reception status for every data packet within a batch. The paper outlines the results of two experiments that involved transmitting agricultural monitoring images where they demonstrate around 25% less time to transmit images compared to pura LoRa protocol. While there is a significant improvement in the transmission time, the implementation of this protocol requires a complete overhaul in the LoRa gateways and nodes, which could be a high capital cost.

The research conducted by Villarreal et al. on transmission of images in the municipality of Covarach´ıa, Colombia presents a study carried out using the Xirio online software in which coverage of LoRa communication is simulated [9]. They present the simulation of a LoRa link between two points with the line-of-sight propagation calculations. They analyze a situation where the critical point signal attenuation levels are not viable to carry out the transmission. They have decided that at this point it requires a signal repeater to be able to regenerate the signal and reach the final destination with reliable levels of transmission. With the simulation, they have been able to identify the areas where the probability of transmitting images is close to zero and areas where the values of the transmission signal levels are at appropriate values to carry out the image transmission process successfully.

A study done by Jebril et al. on a new method for mangrove forest monitoring in Malaysia, wherein they transfer image sensor data over the LoRa communication in a node-to-node network model [10]. In this method, the collected data by the sensors are encrypted as hexadecimal data and then split into packets for transfer via the LoRa links. The transmission, however, takes more than one minute to finish over the air.

Furthermore, the work reported in [11] presents a LoRa-based image transmission system for identifying diseases in grape leaves. The remote sensors with cameras capture low resolution images and transmit them via LoRa to a central location for analysis. Deep learning-based analysis is conducted on the leaf images to detect any diseases building up. They have used the JPEG file format for the images and the transmission frequency is set to 868 MHz.

As it can be seen from the existing literature, there is a growing interest to transmit images via LoRa and in addition to that processing the images using the machine learning capabilities of edge computing is highly sought after.

III. Proposed Architecture

The proposed system architecture is depicted in Fig. 2. The LoRa nodes which are usually deployed in remote locations are equipped with power management modules to operate the batteries and solar panels (if applicable). The camera module will take the images at the interval set by the application requirements. Further, the processing unit carries out the image compression. Finally, the LoRa transceiver is used to transmit the images to the LoRa gateway.

The LoRa gateway stands between the edge computer and the LoRa nodes. The LoRa gateway is expected to have both LoRa and Wi-Fi or Ethernet connectivity. This allows the LoRa gateway to operate as both the LoRa gateway and network server of the typical LoRaWAN architecture [12]. The operation of the LoRa gateway is to receive the LoRa packets and concatenated them to form a Internet Protocol (IP) packet. The IP packet can then be sent to the edge computer via Wi-Fi or Ethernet.

Finally, the data is received at the edge computer where the application level processing would happen. The edge computer has high processing power and storage capacity to handle data coming from a massive sensor network. The machine learning (ML) libraries are used by the app to process the images and draw conclusions. It is worth noting that, although we have shown one app in Fig. 2, there will be many other apps in the edge computer carrying out various other services such as surveillance video processing.

The hardware implementations of the proposed architecture are shown in Fig. 4 and Fig. 5. The LoRa sensor node shown in Fig. 4 features an RA-02 LoRa module from AI Thinker Technology which is based on the Semtech

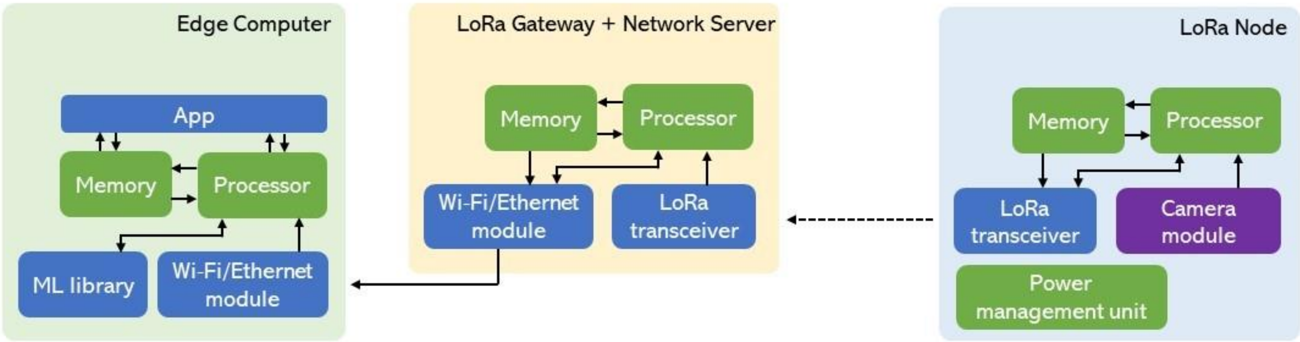
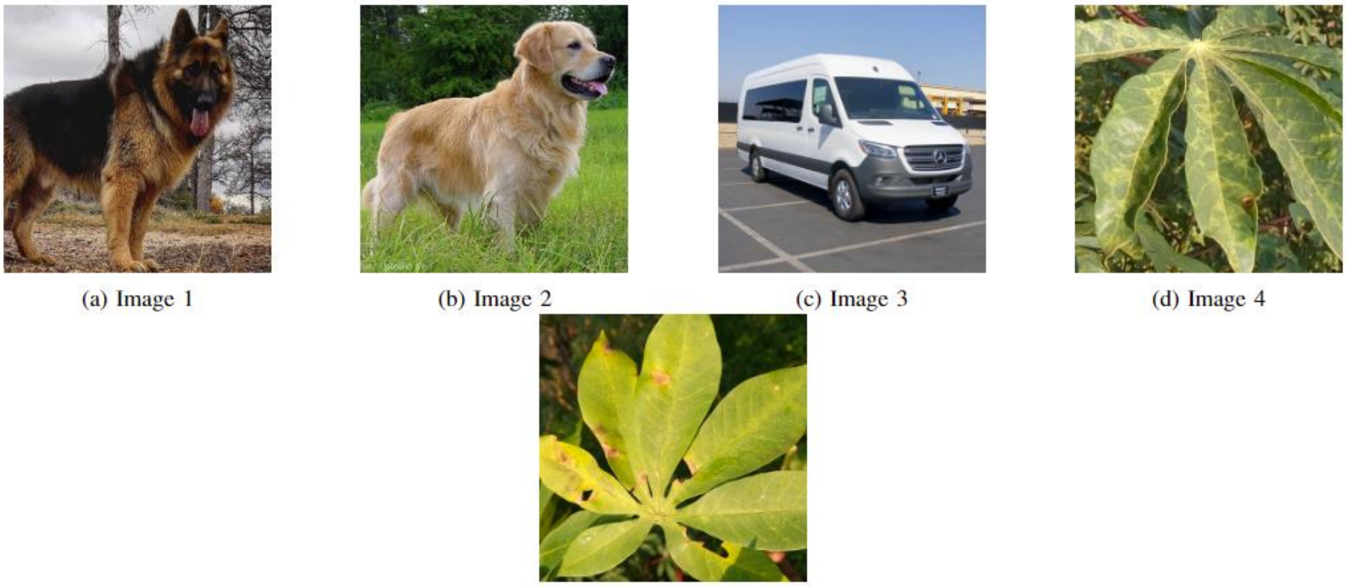


Fig. 2: Proposed System Architecture.



(a) Image 1

(b) Image 2

(c) Image 3

(d) Image 4

(e) Image 5

Fig. 3: Experimental Images.

SX1278 chip [13]. This particular module operates at 433 MHz. In addition to that, the node is equipped with an ESP32-CAM module which contains the OV2640 camera module from OmniVision. Further, the sensor node contains an antenna and a power supply module.

On the other hand, the LoRa gateway has an ESP32 module with an RA-02 module to receive the data coming from the sensor nodes. The edge computer in implemented in an Ubuntu laptop and the gateway connects to the edge computer via Wi-Fi.

IV. Performance Evaluation

In order to evaluate the performance of the proposed architecture several experiments were conducted using the implemented hardware setup. The images shown in Fig. 3 are used in these experiments in the JPEG (Joint Photographic Experts Group) format. The images 1 to 3 are common images that are found in day-to-day applications while the images 4 and 5 are pictures of leaves. The latter two images are specifically used to evaluate the performance of the system for agricultural applications. The following subsections will provide detailed explanation of the experiment and the results.

A. *Image Size vs Compression Quality Factor*

JPEG image format is a lossy image compression type which is widely used in the web and digital photography. The JPEG compression level is measured using the compression quality factor. For instance, an image with 100% compression quality factor has almost no loss (or compression). On the other hand, an image with 10% compression quality factor is a low quality image with loss.

The image sizes variation with compression quality factor are shown in Fig. 6. As it can be seen, without any com pression (100%), the images are in the range of 50 kB to 100 kB. However, once the images are compressed slightly (90%), the image size drops drastically to below 50 kB range. From that point onwards, the drop is slower, however, when the compression quality factor is below 20%, the image size is below 10 kB which is a suitable value for LoRa transmission. Furthermore, almost all the images are affected the same way in the compression process.

B. *Image Quality vs Compression Quality Factor*

Due to its lossy nature, JPEG algorithm makes some trade-offs to lower the image size. To analyze the effect of compression, image quality metrics are used, which can track unperceived errors as they propagate through an image processing pipeline. In this experiment we have used mean squared error (MSE) and structural similarity index to evaluate the compressed images against the original image. MSE measures the average squared difference between compressed and original pixel values. A lower MSE value indicates greater similarity between the two images. On the other hand, SSIM extracts 3 key features from an image which are luminance, contrast and structure into a single local quality score. In this metric, structures are patterns of pixel intensities, especially among neighboring pixels, after normalizing for luminance and contrast. Since the human visual system is good at perceiving structure, the SSIM quality metric agrees more closely with the subjective quality score. The SSIM values ranges between 0 to 1 and 1 means perfect match with the original image.

TABLE I: PARAMETERS OF THE HARDWARE SETUP

Parameter	**Value**
LoRa Module	SX1278
Frequency	433 MHz
Bandwidth	500 kHz
Spreading Factor	6
Transmission Power	14 dBm

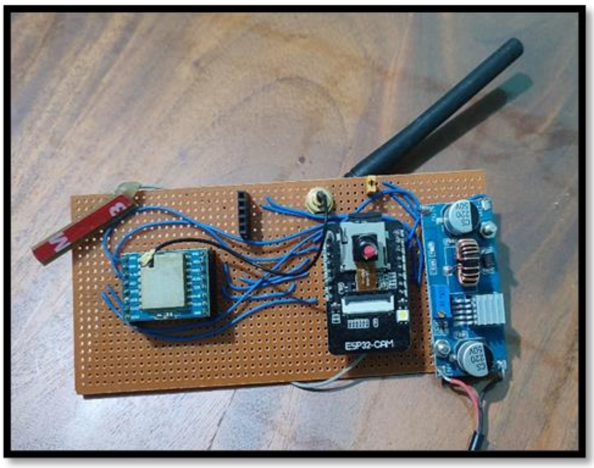


Fig. 4: LoRa Sensor Node Implementation.

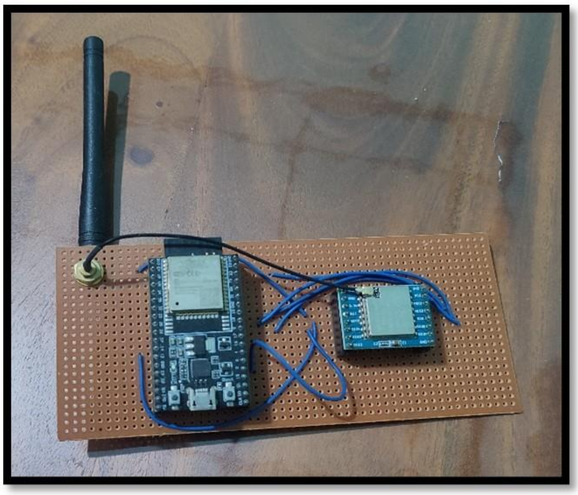


Fig. 5: LoRa Gateway Implementation.

As it can be seen from the Fig. 7, the images experience an increase in the MSE with decreasing compression quality factor. Further, different images are affected in different degrees from the compression operation. Similarly, SSIM also drops when compression quality factor is reduced. However, still the SSIM is above 0.8 for almost all the images which means the structure of the images are not affected adversely.

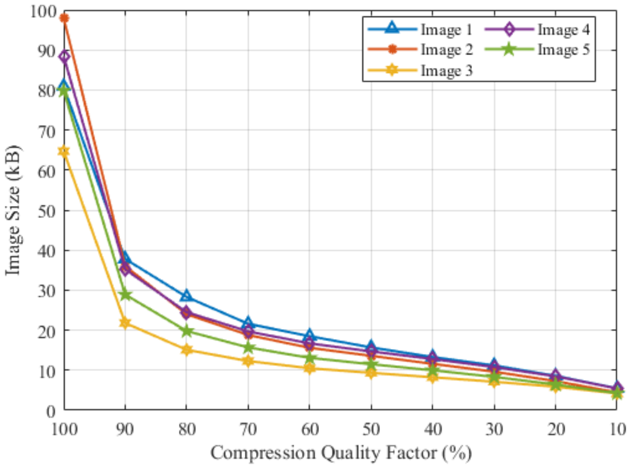


Fig. 6: Image size vs JPEG quality parameter.

C. *Transmission Time*

Next, the compressed images are transmitted through the implemented link and the transmission time is observed. In this experiment, the distance between the transmitter and receiver are set to 3 m as we are not planning to evaluate the effects of propagation channel. The spreading factor is set to 6 and the bandwidth is 500 KHz.

Figure 9 shows the transmission times of the images for varying compression quality factors. At the beginning, without compression, each image takes more than 200 seconds (more than 3.3 minutes) to reach at the receiver. However, the LoRaWAN standard limits the duty cycle of the LoRa devices to 1%, which means that every hour any device can only transmit for 36 seconds [14]. When the compression quality factor reaches 20% and below, it can be seen that the proposed system achieves this duty cycle requirement.

When the compression quality factor is at 20%, all the images can be transmitted in less than 30 seconds. Moreover, if 10% compression quality factor is used, the transmission takes less than 20 seconds.

D. *Prediction Confidence*

Finally, we have evaluated the prediction confidence of the received images using the following five representative neural networks. There are many architectures in the literature and the networks that are tested here represent standard common architectures.

- Resnet50 Prediction Confidence
- InceptionV3 Prediction Confidence

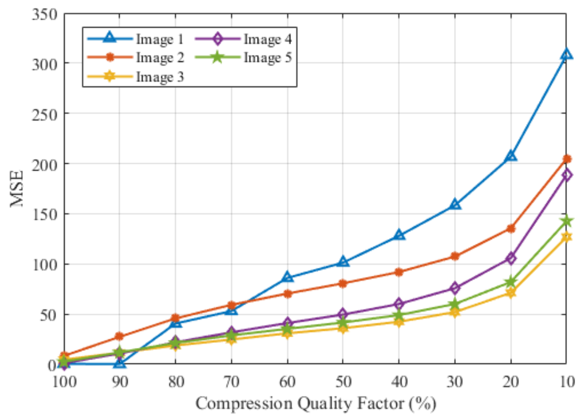


Fig. 7: Mean squared error vs JPEG quality parameter

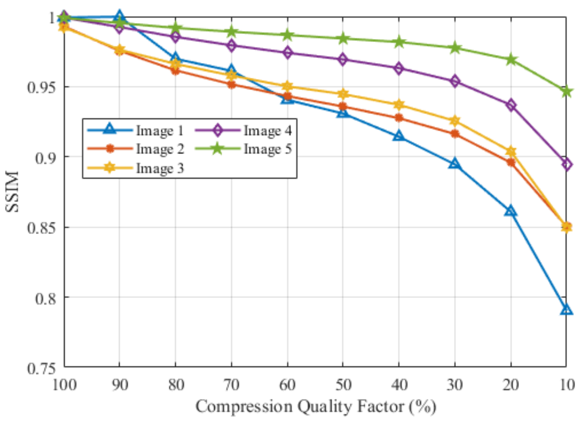


Fig. 8: Structural similarity index measure vs JPEG quality parameter.

- VGG-16 Prediction Confidence
- MobileNet Prediction Confidence
- CropNet Prediction class

The first four of these networks have been trained on the ImageNet dataset [15] and the CropNet model is trained on cassava dataset from TensorFlow datasets [16]. Pre-trained model weights from the TensorFlow library used here for the inference tests and following graphs show how they performed on selected images with confidence variation and JPEG compression quality parameter.

The image 1 to 3 are tested using the first four neural networks while the image 4 and 5 are tested only using the CropNet neural network. The prediction confidence results shown in the Table II. Overall, the prediction confidence is quite high despite the image compression. However, VGG-16 and MobileNet networks outperform the rest of the networks by a small percentage. The leaf detection networks consistently maintain a 60-70% confidence despite the image compression level. This proves that the ML algorithms are capable of operating with the images transmitted through LoRa links with minimal quality.

It is clear from these experiments that LoRa communication networks are suitable for image transmission for edge learning. The tolerance of machine learning algorithms enable the transmission of low quality images in a very common JPEG image format.

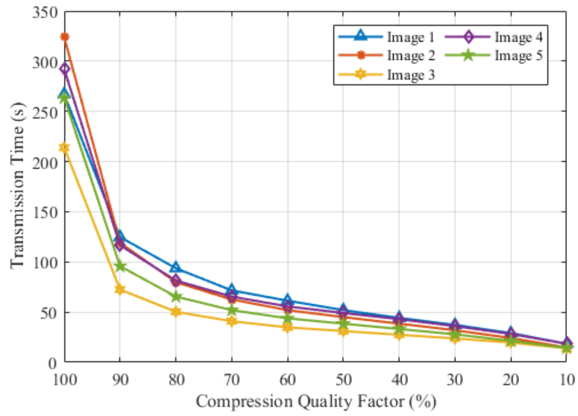


Fig. 9: Transmission time vs JPEG quality parameter.

V. Conclusions

Image transmission using LoRa networks was not considered as a viable solution due to the low data rates of the LoRa protocol. However, since the machine learning algorithms are quite tolerant to low quality images, there is an increased interest in evaluating architecture for LoRa-based image transmission for sensor networks. Especially, with the edge computing facilities, these images are promptly processed at the network edge without burdening the core network. This study explored the possibility of JPEG image compression at the sensor end and transmission via a LoRa network for edge learning. As the results of the practical implementation suggest, it is possible to transmit images with adequate quality for the machine learning algorithms at the network edge. Furthermore, the transmission times are below the duty cylce limits of the LoRaWAN standard which allows global deployment by complying with the regulations.

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TABLE II: PREDICTION CONFIDENCE VALUES.

	Resnet50 Prediction Confidence					**InceptionV3 Prediction Confidence**					**CropNet Prediction class**		
Quality Factor	Image 1	Image 2	Image 3	Image 4	Image 5	Image 1	Image 2	Image 3	Image 4	Image 5	Image 1 to Image 3	Image 4	Image 5
100	0.998298	0.841623	0.812662	-	-	0.892517	0.92862	0.919014	-	-	-	0.650676	0.714968
90	0.998317	0.863559	0.819188	-	-	0.899031	0.927399	0.929099	-	-	-	0.662011	0.715903
80	0.998983	0.852113	0.806023	-	-	0.899416	0.89753	0.926733	-	-	-	0.656987	0.724957
70	0.999163	0.868417	0.816474	-	-	0.874701	0.888743	0.946649	-	-	-	0.643856	0.720553
60	0.998222	0.857489	0.855038	-	-	0.902118	0.88434	0.946842	-	-	-	0.635021	0.721293
50	0.997444	0.868355	0.902772	-	-	0.943397	0.876879	0.945506	-	-	-	0.63654	0.720791
40	0.997682	0.832318	0.92286	-	-	0.93287	0.805331	0.954776	-	-	-	0.643998	0.72341
30	0.999461	0.861005	0.854687	-	-	0.893251	0.871921	0.946942	-	-	-	0.659998	0.71509
20	0.99802	0.884566	0.879493	-	-	0.899512	0.808562	0.928977	-	-	-	0.671774	0.717134
10	0.998821	0.895358	0.857123	-	-	0.886522	0.834488	0.957101	-	-	-	0.658325	0.708265
	VGG-16 Prediction Confidence					**MobileNet Prediction Confidence**							
Quality Factor	Image 1	Image 2	Image 3	Image 4	Image 5	Image 1	Image 2	Image 3	Image 4	Image 5			
100	0.897372	0.88961	0.883141	-	-	0.962858	0.997428	0.964938	-	-			
90	0.898327	0.892263	0.878319	-	-	0.965881	0.996689	0.980842	-	-			
80	0.921429	0.885192	0.888457	-	-	0.976933	0.996754	0.984547	-	-			
70	0.927654	0.889084	0.881973	-	-	0.971868	0.996926	0.97768	-	-			
60	0.931341	0.90026	0.895678	-	-	0.925513	0.995927	0.987416	-	-			
50	0.907743	0.88247	0.902343	-	-	0.975492	0.994488	0.970976	-	-			
40	0.949631	0.896659	0.888481	-	-	0.977986	0.994241	0.966107	-	-			
30	0.943063	0.940011	0.833767	-	-	0.980937	0.994843	0.950074	-	-			
20	0.972943	0.947449	0.892753	-	-	0.976794	0.993798	0.974429	-	-			
10	0.962373	0.93631	0.750307	-	-	0.980564	0.960686	0.935329	-	-			

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