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Nuisance Aquatic Plant Species Identification on Nvidia Jetson Nano Using Computer Vision and Deep Learning

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BACKGROUND

- Currently, identification and classification of nuisance species are done visually and only by people with great experience and skills
- This requires a considerable amount of time and resources
- Very few people have knowledge and skills regarding invasive species classification

RESEARCH GOALS

1. To automate the process of identification and classification using computer vison

2. Configure a Nvidia Jetson Nano microcontroller for real-time in-situ species identification

OBJECTIVES

- Collect image data for 8 nuisance plants commonly found in Mississippi: **Alligatorweed, Cuban bulrush, Giant Salvinia, Water Primrose, Torpedo Grass, Water Hyacinth, Water Lettuce, and White Water Lily**
- Train various neural networks (**CNN and Resnet18**) to simultaneously identify and classify different species efficiently
- Test all networks' performance on new pictures of the eight species to select the best network for this task
- Configure a **Nvidia Jetson Nano** microcontroller with the best trained network to perform real-time object classification and detection using attached camera

METHODOLOGY

I. Data Collection:

- Images were taken in RGB channels using handheld DSLR camera
- 250 images taken for each of the 8 plant species

Figure 1: 8 Invasive Plant Species

II. Deep Learning Model:

- A CNN and Resnet18 networks were used
- Input images were scaled to 224x224 pixels
- Network trained and validated on 1440 and 160 images respectively
- Testing conducted on 400 total images

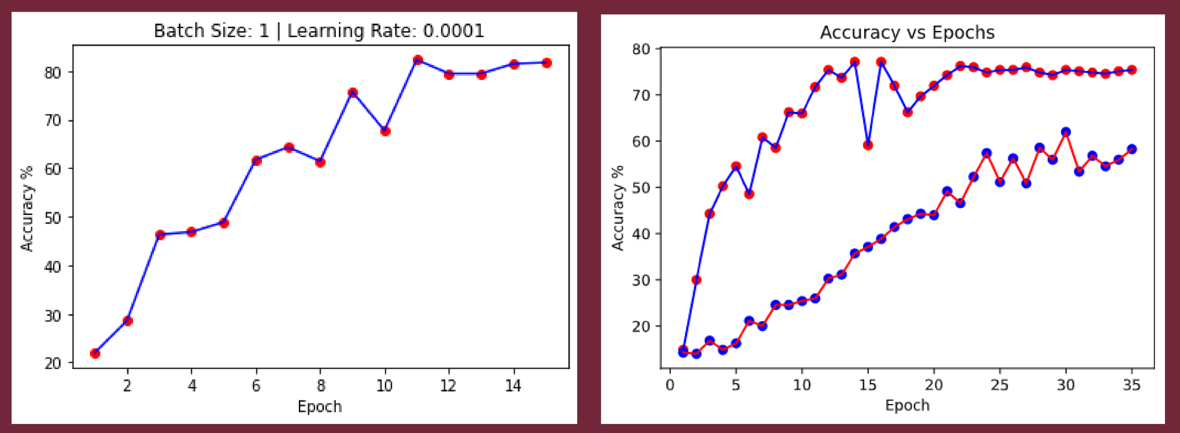

Figure 2: Hyperparameters Tuning and Validation

III. Nvidia Jetson Nano Integration:

- Transfer learning was performed on-device using ImageNet classification model
- Inference done on-device using the trained network and static images stored on the device
- A raspberry pi camera used for real-time live inferencing using ImageNet and TensorRT

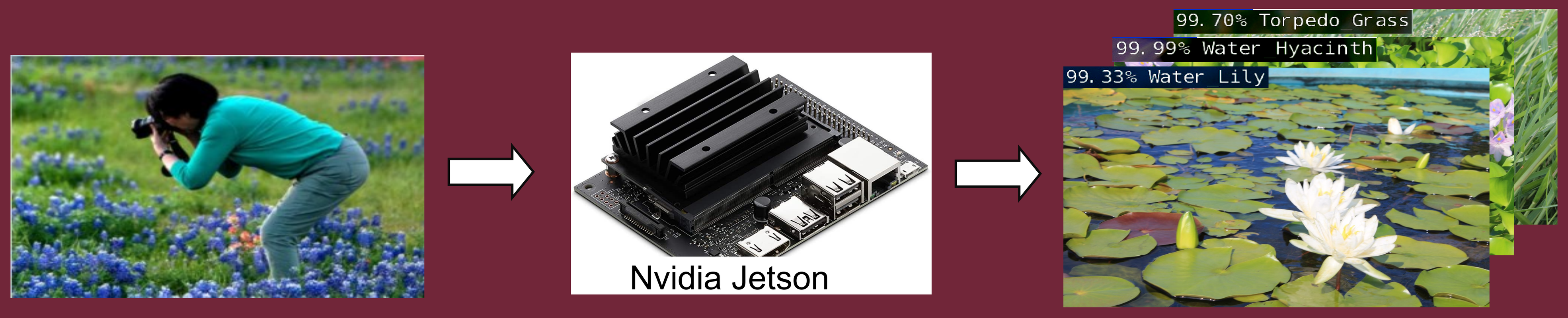

Figure 3: On-Device Classification Process

RESULTS

- A maximum test accuracy of **92.25%,** i.e., 369 correct classification out of the 400 test images
- On-device classification was performed effectively

Figure 4: On Device Classification Results

CONCLUSION

- Deep Neural Network proved to be an effective method for classifying nuisance aquatic plant species
- The trained model integrated well with the Jetson hardware and functioned efficiently

DISCUSSION

- In the future, more species will be added to this model, broadening its application
- Nvidia Jetson Nano can be integrated with an autonomous boat to perform on-the-fly species identification with geotags
- Geotags can be used to create a map that could help in predicting and managing the spread of nuisance species

Figure 5: Classification Model Deployed in Field Setting