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Grasp State Classification in Agricultural Manipulation*

Benjamin Walt[1] and Girish Krishnan[2]

***Abstract*— The agricultural setting poses additional challenges for robotic manipulation, as fruit is firmly attached to plants and the environment is cluttered and occluded. Therefore, accurate feedback about the grasp state is essential for effective harvesting. This study examines the different states involved in fruit picking by a robot, such as successful grasp, slip, and failed grasp, and develops a learning-based classifier using low-cost, computationally light sensors (IMU and IR reflectance). The Random Forest multi-class classifier accurately determines the current state and along with the sensors can operate in the occluded environment of a plant. The classifier was successfully trained and tested in the lab and showed 100% success at identifying slip and grasp failure and 80% success identifying successful picks on a real cherry tomato plant. By using this classifier, corrective actions can be planned based on the current state, thus leading to more efficient fruit harvesting.**

I. Introduction

Interest in agricultural robotics is rapidly expanding. This is driven largely by the desire to increase sustainability and dealing with labor shortages [1]. Many crops, including tomatoes, are harvested manually making them hard hit by labor shortages [2]. These factors make overcoming the challenges of agricultural robotics an important area of research. One of the major challenges for the successful use of robots in agricultural, is the cluttered, occluded nature of the environment [1]. This makes manipulation particularly hard. In addition to the problems of perception and path planning, once the target is grasped it presents a problem somewhat unique to agriculture - attachment. A robot picking up a tomato in a kitchen need only worry about the external force of gravity and avoiding collisions, but when grasping a tomato on a plant the connection to the plant via a stem provides a difficult to predict external force [3]. Furthermore, for a successful picking, a separation event must occur.

Fig. 1 shows the states and transitions that can occur during agricultural manipulation from the initial closing of the gripper to the end state of either *failed grasp* or *successful pick*. To reach an ending state one or more of the intermediate states - *slip* or *no slip* - must be transitioned through - possibly looping several times. In order to achieve efficient and thorough harvesting of fruit it is necessary to have feedback about the current state. With this information, it is possible to correct for a slip prior to losing grasp, reattempt when the grasp has failed or quickly deposit the picked fruit if successful.

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[1]Benjamin Walt is with the Department of Mechanical Science & Engineering, University of Illinois, Urbana-Champaign, USA walt@illinos.edu

[2]Girish Krishnan is with the Department of Industrial & Enterprise Systems Engineering, University of Illinois, Urbana-Champaign, USA gkrishna@illinois.edu

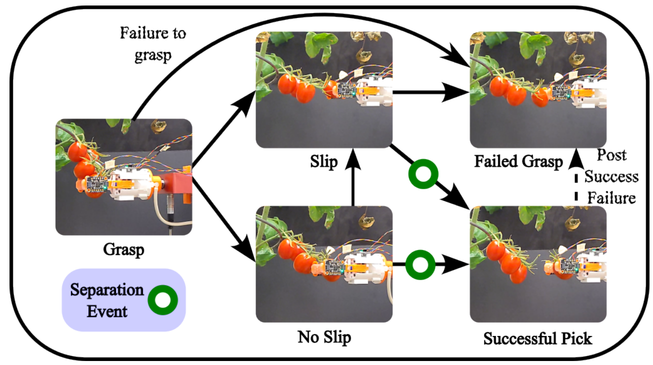

Fig. 1. States transitions during manipulation. Grasp is the starting state and either *failed grasp* or *successful pick* is the ending state. To reach an ending state one or more of the intermediate states must be transitioned through. Dashed lines indicate possible, but less common transitions.

It is natural to see cameras and computer vision solutions to some of these issues [4], [5], however the occluded nature of the agricultural environment will limit their usefulness. Adding numerous cameras and mounting them on their own arms may solve this problem, but only by adding additional complexity. Furthermore, successful, high speed harvesting of fruit will likely require multi-armed robots working in tandem [6], [7] which only adds to the number of cameras needed. In this paper, we propose the use of inexpensive and computationally light sensors and algorithms to determine the current state of the grasping process in agricultural environments.

A. IMU and IR Sensors

The primary sensor we propose to use is an Inertial Measurement Unit or IMU which contains an accelerometer and gyroscope and thus provide linear and rotational acceleration data about three axes. These sensors not only provide information about movement of the sensor, but also can detect vibrations due to small slip events. Additionally, we have included an infrared (IR) reflectance sensor which consists of an LED IR emitter and a photo transistor IR receiver. This sensor detects the amount of IR light reflected back by an object in front of the sensor. It can give a sense of how close an object is to the sensor and changes in position.

B. Classification Problem

We wish to take the sensor data and create a classifier ($\mathcal{C}$) such that for a given set of sensor data at time t, x_t, $Y = \mathcal{C}(x_t)$, such that:

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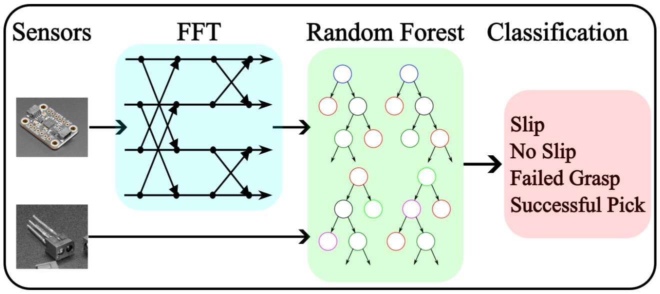

Fig. 2. Pipeline of classifier. IMU and IR data are collected, IMU data is passed to an FFT and along with IR passed to a Random Forest classifier which returns the state of the grasp.

$$\mathcal{C} : \mathbb{R}^{nxm} \rightarrow \{\textit{slip, no slip, successful pick, failed grasp}\}.$$

Where n is the number of features (sensor data) and m is the window size of the data. Instead of using sensor data from a single sample, the IMU data was shifted to the frequency domain using the Fast Fourier Transform (FFT). The input to the FFT was a 25 sample (approximately 0.17 seconds) window of sensor data. IR sensor data was not transformed to the frequency domain as the data is not periodic. Shifting to the frequency domain has been shown to be helpful in identifying conditions such as slip as there is a strong correlation between slip and vibration frequency [8]. A 25 sample window was selected based on a desire to minimize the delay in analysis and ensure that it can be applied to an online controller. Larger windows (50 and 75 samples) were tested and showed only minimal improvement, but with double and triple the delay.

C. Random Forests

The classifier $\mathcal{C}$, was created with a Random Forest (RF) classifier [9]. The RF is an ensemble machine learning method capable of multi-class classification. It uses a large number of Decision Tree classifiers each set up with slightly different parameters. Each tree works with subsets of the feature and data sets to develop a consensus about the classification of an input. Random Forests have been shown to be quite successful in slip detection problems and are well designed for multi-class classification problems. They are also straightforward to implement and it is easy to tune their hyperparameters.

This work focuses on applying established effective methods to the unique problems encountered in agricultural manipulation. We also extended the work beyond slip detection to provide feedback on the current state of the grasp through the whole process. The **contributions** of this work are: 1) A classification model capable of determining the current state of the grasp in agricultural environments. 2) The ability to detect key events such as the failure to grasp an object, slip, grasp failure, and separation of the fruit from the plant. 3) A model that works with low-cost and computationally light sensors. 4) A model that has been trained in the lab, but demonstrated to work on a live plant.

II. Related Work

Research into slip detection has a long history and excellent surveys of methods and sensors can be found in [10] and more recently [8]. A wide variety of techniques have been explored, but we will focus on those using IMUs, Random Forest classifiers and slip detection in agriculture.

A number of recent works have shown the benefits of using IMU for slip detection. IMU were combined with capacitive tactile sensors by [11] to provide both exteroception and proprioception in assessing grasp stability. [12] showed effective classification and prediction of grasp failure by applying 16 IMUs to soft and compliant hands and processing it with a combination of CNN and Long Short-Term Memory (LSTM) networks. By using two IMU, [13] was able to measure the relative angular velocity between them and detect vibrations to predict slip. [14] used an IMU in conjunction with a Random Forest classifier to develop a proxy apple for learning to predict picking success. [15] created a custom gripper for apple harvesting with a multimodal tactile sensor that included IMU on each finger. This was used to perform state estimation of the underactuated fingers with the goal of better understanding and quantifying grasp quality. The authors suggest this data could be used to detect key events in the picking process, but do not test this.

Much work has been done to demonstrate the promise of Random Forest classifiers for slip detection. [16] used RF combined with feature functions on a multimodal BioTac tactile sensor to stabilize grasps. Predictions about future sensor readings were made in [17] by using various Neural Nets models. These predictions were based both on current sensor data and manipulator actions and were passed to an RF classifier to make predictions about future grip stability.

While agricultural manipulation has an established history, research into slip detection in agricultural environments has seen a more recent growth. [18] developed a slip sensor based on a resistive force sensor. This was used to create a controller to maintain the minimum force needed to prevent damage to the fruit while overcoming grasp failure. The problem of slip due to leaf interference in apple harvesting was investigated in [19]. They applied tactile sensors to compliant Fin Ray effect fingers and used a LSTM neural network to detect and respond to slip. [20] also developed a Fin Ray effect gripper for apple harvesting. By use of tactile sensors and using feedback to maintain a constant force on the fruit, they were able increase the harvesting success rate and minimize damage to the fruit.

While these tactile methods have shown great promise in slip detection and avoidance, there is an need for a more holistic view of grasp state. Such a view would look at grasping from beginning to end and allow effective feedback of the current state.

III. Experiments and Data Collection

A. Sensors and Hardware

Testing was done on a 6DOF xArm6 (uFactory) fitted with a custom pneumatically actuated two-fingered gripper. The gripper (Fig. 3f) was 3D printed from PLA and

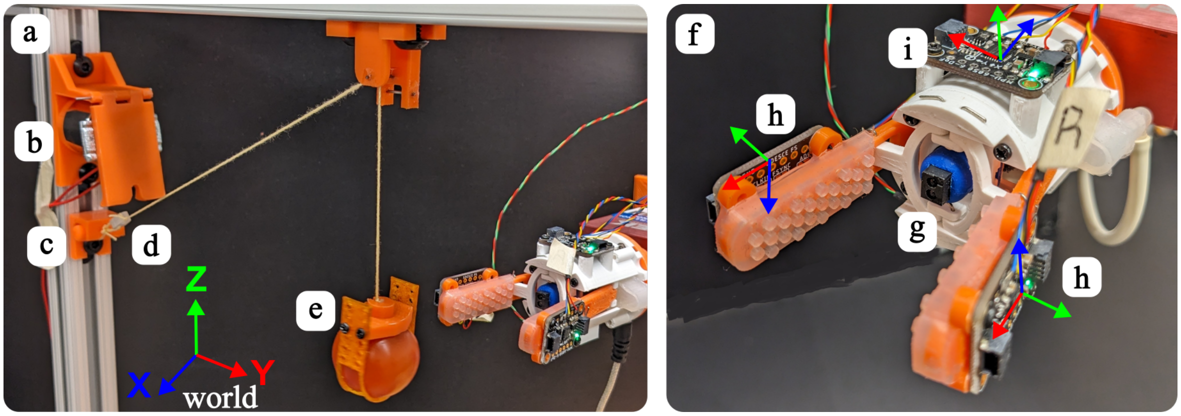

Fig. 3. Hardware use in data collection and testing. a) training rig b) quick release mechanism c) fixed mount d) compliant link e) fruit mount f) gripper detail g) IR sensor h) finger IMU i) body IMU

designed specifically to work in the cluttered environment of a cherry tomato plant. The fingers are coated with a textured, knobby surface made from Dragon Skin 20 silicone (Smooth-On Inc.) The gripper is fitted with three MPU6050 IMU sensors (Adafruit) and one ITR20001/T IR reflectance sensor (Adafruit). One IMU was mounted on each finger (Fig. 3h). Since the fingers were fixed on one end to a soft pneumatically actuated bladder, they were not rigid and can experience small movements and vibrations during grasping. The third IMU was rigidly mounted on the gripper body (Fig. 3i). The IR sensor was mounted in the throat of the gripper (Fig. 3g). Data collection was completed at 150Hz using an Arduino Mega 2560 connected to an Intel NUC7i7 running Ubuntu 18.04 and ROS Melodic. A TCA9548A I2C multiplexer (Adafruit) was used to handle address collisions with the three IMU. Additionally, a Futek LRF400 load cell was placed between the arm mount and the gripper to measure the axial pulling force. This force was used only for labeling of the training and testing data sets and was not part of the classification pipeline.

B. Data Collection Method

1) Experimental Set Up: To collect training and testing data, a cherry tomato was fixed in a mount (Fig. 3e) that allowed it to be connected via a string to a rigid support (Fig. 3a). The mount was designed to minimize interference with data collection allowing full contact between the gripper fingers and the sides of the fruit and a clear path between the IR sensor and the fruit. The other end of the string was attached either to the rigid support frame (Fig. 3c) or to a quick release mechanism consisting of an electromagnet actuated by a relay (Fig. 3b). With the string fixed to the frame, it was possible to simulate grasp failure and with the quick release mechanism, it was possible to simulate the separation of the fruit from the plant. A small compliant link made of Dragon Skin 20 silicone was inserted between the string and connector to simulate the compliant nature of stems and pedicels of the plant (Fig. 3d).

2) Data Collection: To collect data, the open gripper was positioned with the target well placed between the fingers. At this point the gripper closed on the target and the automated process of data collection began. The target would be pulled (negative X direction) and lifted to keep the axis of pulling along the length of the fingers. The trajectory would vary in both speed (15-25mm/s) and final position with the values being determined randomly. It was horizontally pulled 180mm in the negative X direction while the final Y position would vary by $\pm$40mm and the final Z by $\pm$15mm. For a *failed grasp* trial, the string would be hooked on the rigid support and the target would naturally slip from the grasp. For a *successful pick* trial, the string would be hooked on the quick release mechanism and be released by the operator during the high tension pulling phase. A human operator introduced some variation in when and under what conditions the separation occurred. Data collection stopped when the arm reached its final pose regardless of outcome. The rig could then be rapidly reset for the next data collection trial. The target tomato was periodically replaced to ensure that variations in size and texture were accounted for as well as any deterioration of the tomato due to handling. Collected data was labeled by an expert using custom labeling software that allowed the viewing of collected sensor data including force sensor readings. Based on the data, especially force sensor readings, it was possible to locate the key points such as the beginning and end of slip and the moment of separation or grasp failure.

C. Training and Validation

Three data sets were collected: a training set (250 trials), a validation set (50 trials) and a test set (56 trials) each having approximately one half failed grasps and one half successful picks. A Random Forest classifier was created using Scikit Learn [21] and the hyperparameters and required training set size were tuned using the validation data set. Key values selected: Estimators: 100, splitting criteria: Gini index, and maximum number of features per tree: square root of the number of features. The results of training can be seen in Table I which show a strong ability to correctly classify the state of the grasp. The major confusions, as seen in Fig. 4, occurred between *slip* and *successful pick* and classifying *slip* as *no slip*. It is unsurprising to see these forms of confusion. In the boundary regions as *slip* transitions to *no slip* and vice-versa labeling will be imprecise and the data itself will not always be clear cut. *No slip* and *successful pick* naturally share many characteristics. The big differences being the dampening effect of the string or stem while under tension as well as the change in IR sensor value.

TABLE I
VALIDATION RESULTS

State	Precision	Recall	F1-Score
No Slip	98%	99%	99%
Slip	91%	88%	89%
Failed Grasp	100%	99%	100%
Successful Pick	88%	87%	87%

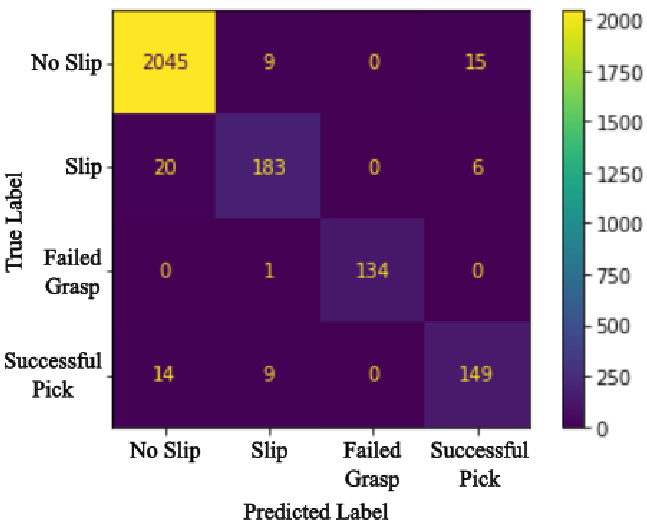

Fig. 4. Validation Data Confusion Matrix

D. Ablation Study

To better understand how the sensor data contributes to classification, an ablation study of the sensors was performed. The RF was trained with subsets of the full (IR + 3 IMU) sensor set. A summary of the F1-Scores can be seen in Table II.

- IR Sensor Only - By itself this sensor performed very well and demonstrates its important role in classification. However, it results in more spurious responses.
- IMU Sensors Only - The full set of IMU sensors also performs well, but sees many spurious responses and has difficulty differentiating between *no slip* and *successful pick*.
- Body IMU Only - This sensor by itself performs notably worse than the full IMU set, but its performance does show that the presence of any IMU is enough to give useful information about the grasping state. This sensor's response was always the weakest of the IMU.
- Finger IMUs Only - These perform nearly identically to the IMU only, suggesting these two sensors are the more important of the IMU sensors.
- Accelerometers and Gyroscope Only - Each performs slightly worse than the full IMU set suggesting that it is an interplay of the two that give improved results.

It is clear that the IR sensor plays a key role - especially in *slip* and *successful pick* identification and differentiation. When combined with the IMU data, it provides a "smoothing" effect in that it minimizes spurious classifications. The precise role of the different IMU is less clear. The body IMU does not play as important a role as the finger IMUs, but the authors suspect it could play a role in disturbance rejection in a more complex set up. Both the accelerometers and the gyroscope work together to give better results, but they do perform strongly on their own. This testing was performed both using the validation data set and the plant data set. While the individual sensors performed reasonably well on the validation data, that did not translate into good performance on the plant data set. This suggests that the combination of sensors also makes the detection more robust when exposed to the more complex data of the plant set.

TABLE II
ABLATION STUDY F1-SCORES

	F1-Score						
Sensor Set	**Full**	**IR**	**IMU**	**Body IMU**	**Finger IMU**	**Accel-erometer**	**Gyro-scope**
No Slip	99%	97%	97%	94%	97%	96%	97%
Slip	89%	87%	67%	41%	78%	64%	71%
Failed Grasp	100%	100%	98%	85%	98%	97%	96%
Successful Pick	87%	84%	65%	57%	76%	70%	75%

IV. RESULTS

A. Testing Data

A total of 56 test data trials were taken - 28 that resulted in separation and *successful pick* and 28 that resulted in *failed grasp*. The classifier showed a strong ability to identify these end conditions correctly. Fig. 5a shows a well performing trial of a failed grasp. *Slip* (red line), closely matches the *slip* truth value (shaded pink area), the failure event is identified shortly after the labeled point (green dashed line), and *failed grasp* (blue line) closely matches the *failed grasp* truth value (shaded light blue area). Fig. 5b shows a well performing trial of a successful pick. *Slip* (red line), closely matches the *slip* truth value (shaded pink area), the separation event is identified shortly after the labeled point (green dashed line), and successful pick (black line) closely matches the *successful pick* truth value (shaded gray area). Table III contains detailed metrics of the test results. Delta values are given in seconds to better understand the potential behavior in a real time set up. *Slip* was identified on average 0.18 seconds after the labeled event, separation was identified 0.19 seconds after the event and *failed grasp* was identified 0.18 seconds after the labeled event. These values include the worst case 0.17 second delay due to the FFT window. Missed events indicate a data type that was labeled, but never classified by the classifier. There were 4 missed *slip* events (discussed below) and no missed *successful pick* or *failed grasp* events. False events occur when a classification is made, but that label does not exist in the trial e.g. a *successful pick* classification on a *failed grasp* trial. There were 3 false *successful pick* events and no false *slip* or *failed grasp* events. Min/Max Delta indicates the minimum and maximum time in seconds between the first label and first matching classification. The worst case values are 0.6 seconds. Analysis of the data showed three common issues:

- Missing *slip* events (Fig. 5c): This occurs when *slip* is labeled, but never detected. All missed *slip* events were short in duration (only one labeled window long) and occurred prior to a separation event. It is likely that this short duration is the cause and would not be an issue for corrective action, which is the goal of slip detection.
- Unsustained *successful pick* detection (Fig. 5c): This occurs when *successful pick* is detected in a timely manner, but all subsequent classification fails. This appears to be the result of a high IR sensor reading after separation. The short duration of *slip* resulted in a higher post separation IR value than was seen in other tests. This made it look more like a *no slip* condition.
- Spurious early or false *successful pick* events (Fig. 5d): These occurred when a single classification event occurred much earlier than the true event or a classification of an event that should not have occurred. An examination of the sensor data and timing showed that this occurs as the target was beginning to rotate and experiencing rotational slip can cause a significant response on the IMU. This response could result in a misclassification.

TABLE III

TEST DATA AND PLANT DATA KEY METRICS RESULTS

Data Set	Testing Data	Plant Data
Total Trials	56	12
Failed Grasp/Successful Pick Trials	28/28	7/5
Missed Slips	4	0
False Slips	0	1
Min/Max Slip Delta (s)	0.06/0.60	0.26/0.66
Slip Delta Average (s)	0.18	0.49
Missed Successful Pick	0	1
False Successful Pick	3	2
Min/Max Successful Pick Delta (s)	0.24/0.40	0.03/0.14
Successful Pick Delta Average (s)	0.19	0.07
Missed Failed Grasp	0	0
False Failed Grasp	0	0
Min/Max Failed Grasp Delta (s)	0.1/0.27	0.25/0.14
Failed Grasp Delta Average (s)	0.18	0.18

B. Plant Data

For a final verification, the classifier was tested on data collected on a real cherry tomato plant (Cherry Roma variety, Burpee Seeds). Data was collected in an identical manner to the training and testing sets with the exception of the need to mount the target on a string. A total of 12 data trials were collected - 7 failed grasp trials and 5 successful pick trials. Table III contains detailed metrics of the test results. *Slip* was identified on average 0.49 seconds after the labeled event, separation was identified 0.07 seconds after the event and *failed grasp* was identified 0.18 seconds after the labeled event. These values again include the worst case 0.17 second delay due to the FFT window. There was 1 missed *successful pick* event (discussed below) and no missed *slip* or *failed grasp* events. There was 1 false *slip* event and 2 false *successful pick* events (discussed below) and no false *failed grasp* events. Min/Max Delta are less than 0.66 seconds. The types of results were similar to the test data results, however the unsustained *successful pick* detection was present in 4 of the successful pick trials (one successful pick trial failed to detect *successful pick* at all). *failed grasp* and *slip* detection were robust with no missed slips (Fig. 5e) and only one spurious *successful pick* detection. The results showed promise in the ability to apply this work to real environments.

- Missed *successful pick* - This trial shows an IR sensor pattern that is quite different than other trials - the value actually rises significantly rather than dropping. Fruit shape may play a role here as the longer, more ovoid shape of the Cherry Roma variety causes the end of the fruit to rotate in *towards* the IR sensor as pulling occurs. This behavior is very distinct from the rounder shape of the Honey Sweet variety used in training.
- Unsustained *successful pick* detection (Fig. 5f) - This appeared again to be due to higher IR sensor readings, but was even more pronounced. The real plants experienced much less slip than was present in the training data which could result in easy confusion between the *successful pick* and *no slip* classifications. Additionally, the initial IR values began much higher and suggest that there is a difference in IR reflectance for the different varieties for which corrections may need to be made.
- Spurious early or false *successful pick* events (Fig. 5g) - This appears to have the same cause as in test data

It is clear that more work needs to be done to effectively classify *successful pick* on real plants. It appears that there is a natural difference in IR reflectivity between the fruit used in training compared to the real plant variety. Fruit shape may also play a role as well.

C. Empty Grasping

A simple heuristic was added to the classification pipeline to further expand it usefulness by detecting if, after the grippers have been closed, an object was actually grasped. This consisted of checking for a *failed grasp* state shortly after the griper was closed (within 200 samples). In addition to the test and plant data sets, this was tested on 25 trials created by performing a picking action without a fruit to grasp. All 25 of these empty data runs were correctly classified as *empty grasps* and none of the test or plant trials were misclassified.

V. CONCLUSION AND FUTURE WORK

In this paper we presented a Random Forest based method to classify the state of grasping in an agricultural environment. It makes use of low-cost, computationally light IMU and IR sensors which have been mounted on a generic, two-finger gripper. The system was trained using a rig to simulate both failed grasps and successful picking and was

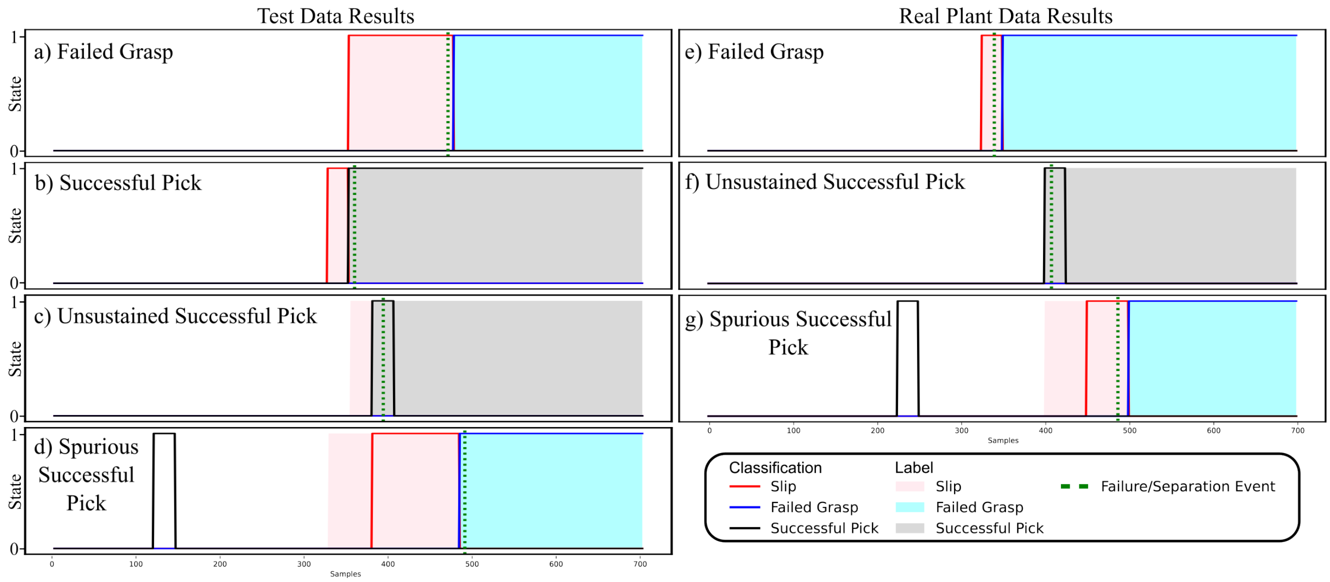

Fig. 5. Example results of the classifier on the test data set (a,b,c,d) and plant data set (e,f,g). Legend for all graphs is in the lower right corner. A high reading indicates the classifier returning the give class or the label assigned. a) & e) show a failed grasp result, b) shows a successful pick, c) & f) show successful picks that are not identified after the initial event, d) shows a spurious successful pick event in what is really a failed grasp.

then tested on a living cherry tomato plant. The results show promising performance for the sensor choice, classification model and training methodology. In our future work, we hope to improve its robustness by working on rotational slip and variations in the IR response. We also hope to implement this work as part of a full grasping pipeline to take corrective action based on the output and recover from unstable grasps. Additionally, we hope to extend the performance to other fruit and gripper designs.

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