



## **SMART DEVICE FOR DETECTION AND CONTROL OF FALL ARMYWORM**

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### **INTRODUCTION**

Agriculture is not only food provider for human existence, but also a big source for the economy of the country. A large portion of the government budget is being spent for the agriculture sector in order to safeguard the crops. Insect pests are dangerous for the overall growth of the crops. Several Integrated Pest Management strategies have been tailored for the effective management of insect pests under field condition. But, a prime method to protect the crop may be the regular monitoring of the crop for the occurrence of the insect pests to understand the health of the crop. Early detection of insect pest infestation to evolve suitable management techniques, therefore, would be an important step towards successful implementation of pest control strategies at appropriate time targeting the most vulnerable stage of the insect pest. Further, if the insect pests are detected at their early stage, appropriate measures can be taken to protect the crop from future damage that can be caused by the insect thereby immense crop loss can be minimized. The added advantage would also the heavy pesticide pressure on the crop, environment and on the natural biota can be reduced to a greater extent. The process of examining the crop for pest infestation is very expensive and time consuming. Hence, an automated technological solution is required to examine the crops for the presence of pest infestation and then classify the type of insect pest affecting the crops.

One such possible solution is computer vision technique for analyzing the digital images of different parts of plant namely leaves, stem, flower and fruits including the different stages of the insects sheltered on the crops for damage. To address the problem, we propose a Smart system for early identification of Pests as a case study we have started with Fall Armyworm using computer vision and Wireless Sensor Networks.



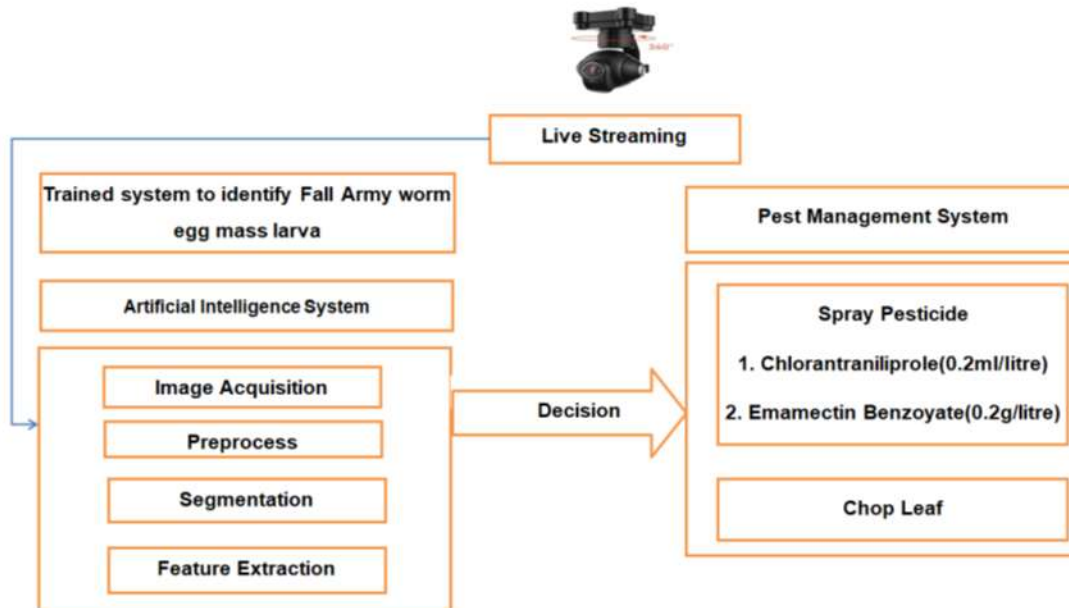
## LITERATURE

The fall armyworm, *Spodoptera frugiperda* (J. E. Smith) (Lepidoptera: Noctuidae) is a polyphagous insect pest that can feed on plants from more than 20 families but it displays a preference for plants of the family Poaceae (Luginbill, 1928; Anonymous, 2018a). Damages are most commonly reported on maize, paddy, sorghum, sugarcane, soybean and cotton (Anonymous, 2018a ; Anonymous, 2018b ; Anonymous, 2018c). The fall armyworm consists of two genetically differentiated strains. They are commonly referred as the rice-strain (R-strain) and the corn-strain (C-strain) (Quisenberry, 1991; Nagoshi and Meagher, 2004). This pest is found in several countries such as Brazil, Argentina, USA, Africa and Asian countries (Prowell et al., 2004; Clark et al., 2007, Abrahams et al., 2017) causing economic losses in a variety of crops. Because of its wide host range, *S. frugiperda* is one of the most harmful pests threatening annual crops in tropical regions (Andrews, 1980; Cruz et al., 1999). This availability of different hosts might even result in the selection of insect populations with new food preferences due to different exposure of these insects to a variety of crops (Barros et al., 2010). Although soybean is not one of the preferred hosts of *S. frugiperda*, it is one of the most abundant summer crops in Brazil, which may favor the establishment and environmental colonization of this crop by *S. frugiperda* (Andrews, 1980; Barros et al., 2010).

## PROPOSED MODULE

An autonomous robot integrated with cameras, computer vision, machine learning and robotics to build an intelligent sprayer that travels through fields and quickly targets different developmental stages of fall army worm like egg mass, larva, pupa and adult moths and sprays the fallarmy worm, leaving the crops intact.

The machine makes real-time decisions on where exactly the fall army worm is located. As the machine travels through the field, our high-resolution cameras collect imagery at a high frame rate. The authors developed a convolutional neural network (CNN) algorithms using tensorflow to analyze each frame and produce a pixel-accurate map of where the pest is located. Once the plants are all identified, fall armyworm stages are mapped to field locations, and the robot sprays only the pest. This entire process happens in milliseconds, allowing the farmer to cover as much ground as possible since efficiency matters



**Figure 1: Proposed System**

Basic biological studies on the consumption and use of different food sources, in addition to those on the host preference of *S. frugiperda* are important for addressing the effects of the nutritional composition of different crops on this pest (Scriber and Slansky, 1981; Barros et al., 2010). However, to the best of our knowledge, this is the first study in India to compare biological characteristics of this pest when fed on different host species grown in different seasons of the year. This is crucial to understand the survival, population increase and infestation of this species throughout the year. With the help of camel hair brush, the first instar caterpillars were transferred into small plastic boxes, the lids of which were provided with mesh for aeration. Three replications were maintained for each treatment. Tender fresh leaves of various host plants were collected from insecticide free plots and fed daily to the neonate larvae in separate boxes. As the growth of the larvae progress, the small boxes were replaced by large plastic containers covered with muslin cloth and fastened by rubber bands. After 5th moult, a thin layer of sand bed was placed inside each container in order to provide suitable condition for pupation. Pupae obtained from different host crops were collected separately and kept for emergence in the glass jars. Emerged moths were collected and maintained separately in adult rearing cage containing fresh leaves of corresponding host crops for egg laying. The entry of the cage was closed with glass plate and inside, 10 per cent honey solution soaked in cotton swab was provided as adult food. After 5-6 days, the leaves containing eggs were taken out and kept for hatching.

**Table 1 List of crops used for host range studies**

Host Crops	Scientific name	Family
Sorghum	<i>Sorghum bicolor</i>	Graminae
Maize	<i>Zea mays L.</i>	Graminae
Cotton	<i>Gossypium hirsutum</i>	Malvaceae
Groundnut	<i>Arachis hypogaea L</i>	Leguminaceae
Napier grass	<i>Panicum purpureum</i> v <i>panicum typhoides</i>	Graminae
Cabbage	<i>Brassica oleraceae</i>	Brassicaceae
Wheat	<i>Triticum aestivum</i>	Graminae

With the help of camel hair brush, the first instar caterpillars were transferred into small plastic boxes (@ 25 larvae/ box), the lids of which were provided with mesh for aeration. Three replications were maintained for each treatment. Tender fresh leaves of various host plants were collected from insecticide free plots and fed daily to the neonate larvae in separate boxes. As the growth of the larvae progress, the small boxes were replaced by large plastic containers covered with muslin cloth and fastened by rubber bands. After 5<sup>th</sup> moult, a thin layer of sand bed was placed inside each container in order to provide suitable condition for pupation. Pupae obtained from different host crops were collected separately and kept for emergence in the glass jars. Emerged moths were collected and maintained separately in adult rearing cage containing fresh leaves of corresponding host crops for egg laying. The entry of the cage was closed with glass plate and inside, 10 per cent honey solution soaked in cotton swab was provided as adult food. After 5-6 days, the leaves containing eggs were taken out and kept for hatching.

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The observations were made on the number of larvae surviving on each host once in 2-3 days, from which per cent larval survivability was assessed. The minimum and maximum period taken for the larval development, pupal period *etc.* were also recorded on different hosts.





### **Pupa Incubation**

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#### **1. Egg mass**

- Eggs - dome shaped
- Dirty white to gray
- Laid in groups - 100-200 eggs per egg mass
- Fecundity - 1000-1500 eggs/ female
- Mostly laid on upper surface of the tender leaves

- Eggs - covered - grayish scales - moldy appearance
- Eggs hatch – 3-5 days



Larva

- Six larval instars
- Fully-grown larva - 3.1 –3.8 cm
- Vary in color - pale green to almost black
- Wider dark stripe and a wavy yellow-red blotched stripe on each side
- Predominant white, inverted Y-shaped suture on the head
- Larval duration – 14-22 days







Adult Larva

### Detection of Pests by Computer Vision and Machine Learning Algorithms Innovativeness

To identify the various stages of Fall Armyworm following machine learning algorithms have been developed using Python Machine Learning Library. To automate this process we build a computer vision system by extracting its local features and training the cascade classifier. This classifier can be hence used for automatic detection of the pest by identifying change in texture and colour. The following are the infestations identified.

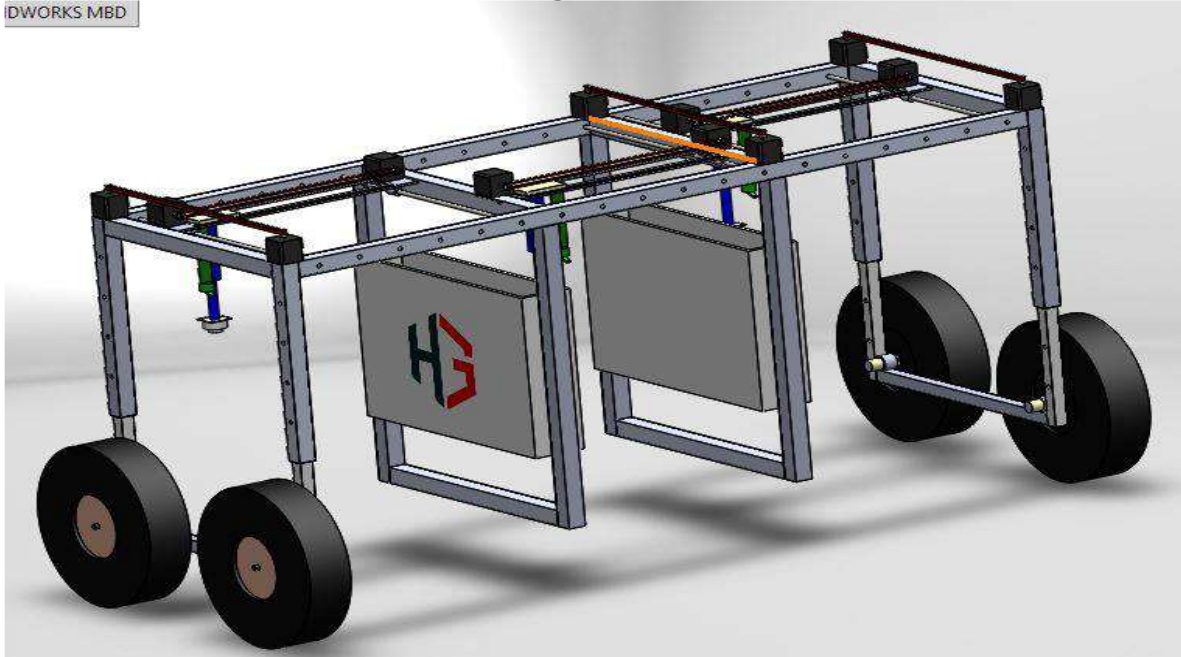
1. Egg Mass
2. Young Larva
3. Adult Larva
4. Pupa

### MECHANICAL DESIGN

#### Dimensions

A 3D model is built as per the design and the original dimension of each component in the design is taken into consideration to estimate the design size. This helps to validate the size and determine the deviation from the given constraint value. It is also important to consider the storage space required. The design was verified from Professors of Entomology Department UAS Dharwad.

DWORKS MBD



### Actual Model



## Methods

To support the machine learning (ML) and robotics stack, we have built an impressive compute unit, based on the Raspberry Pi System on Module System powered by Google's Tensor Flow technology to make an impact.

**To train our CNN, we have undertaken the following steps.**

### Step 1. Training set

The training data set for the CNN will come from the field of University of Agricultural Sciences Dharwad where our researchers have collected images of fall armyworm..

We have collected a sample of 20000 images of fall army worm stages like egg mass, larva, pupa and adult moths

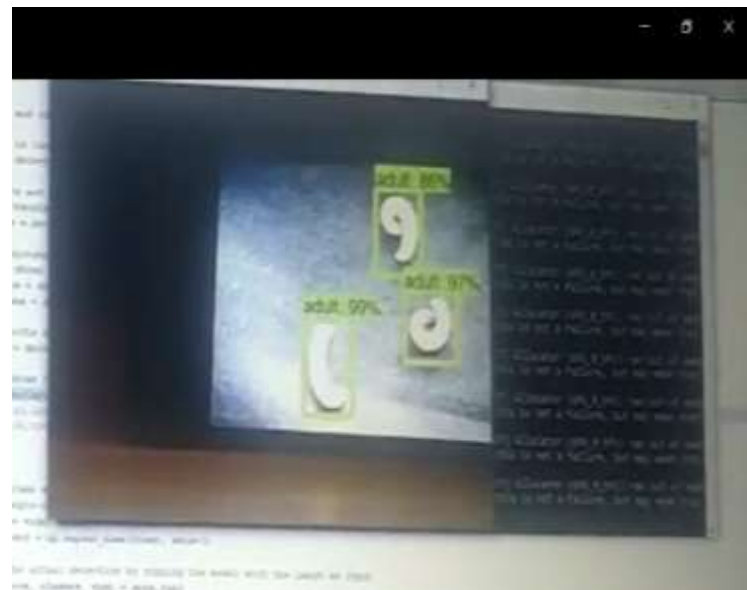
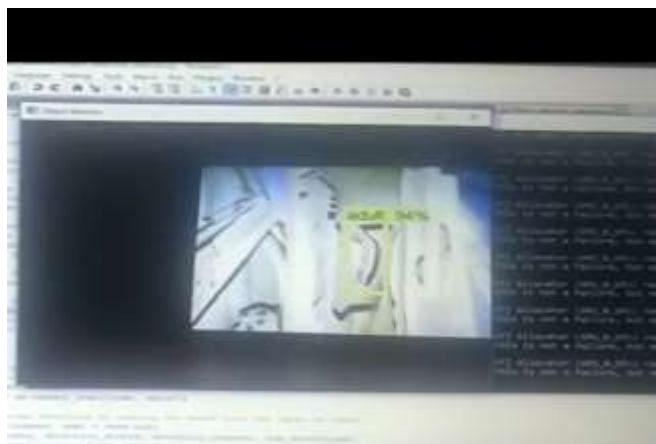
### Step 2. Creating and configuring the Model.

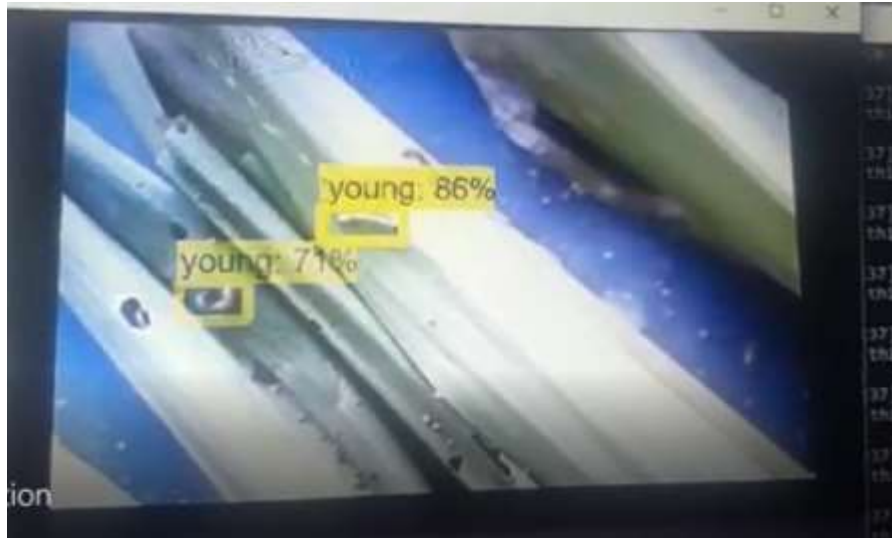
Use of vegetation detection, object-based feature extraction, random forest classification, and smoothing through a Markov random field to accurately classify we have formulated a fully convolutional network (FCN) to encode the spatial information of fall armyworm objects in a row over sequentially acquired image sequence to perform the classification task, resulting in a better runtime performance.

D. Step 4. Deploying models on field robots.

The complete system was integrated onto the robot to travel in the field and identify fall armyworm stages

Results





## CONCLUSIONS & FUTURE SCOPE

All Fall Armyworm invaders were identified by Computer Vision Based programmes powered by Machine Learning Algorithms such as Convolutional Neural Networks, Support Vector Machines, Classifier, SUM, Local Binary Patterns, HSV Image Based Algorithms, Canny Edge Detection Algorithm. This facilitates the automation of the detection of pests in the maize crop which will help the maize growers to the greater extent.

Same frame work can be utilized for diseases and insect pest identification and management in other crops by developing knowledge base. The UI interface can be provided in local language so that the famers can easily interact and take help directly from the module.

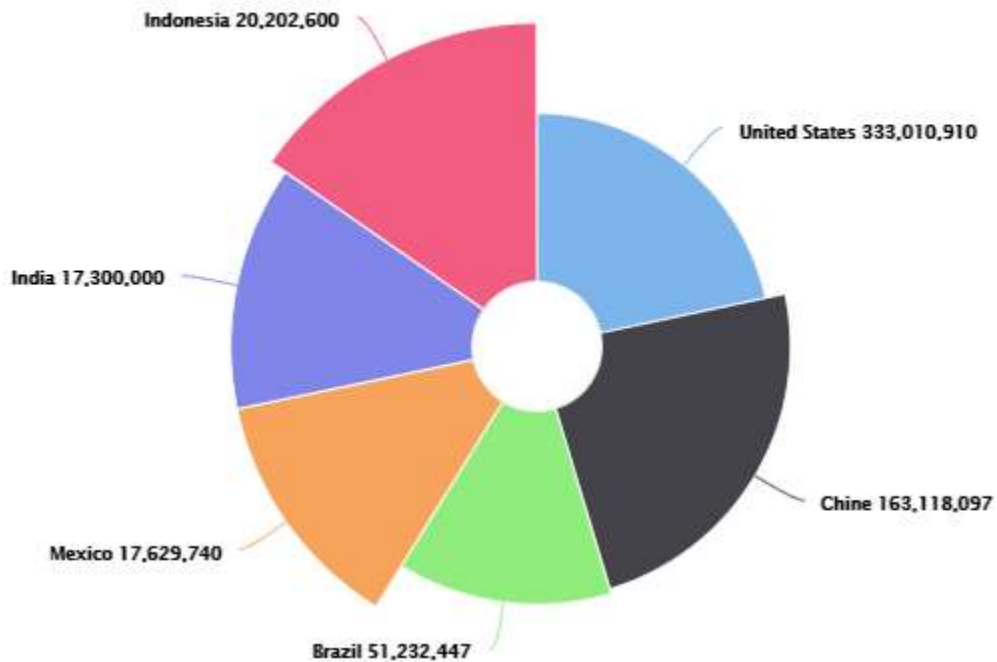


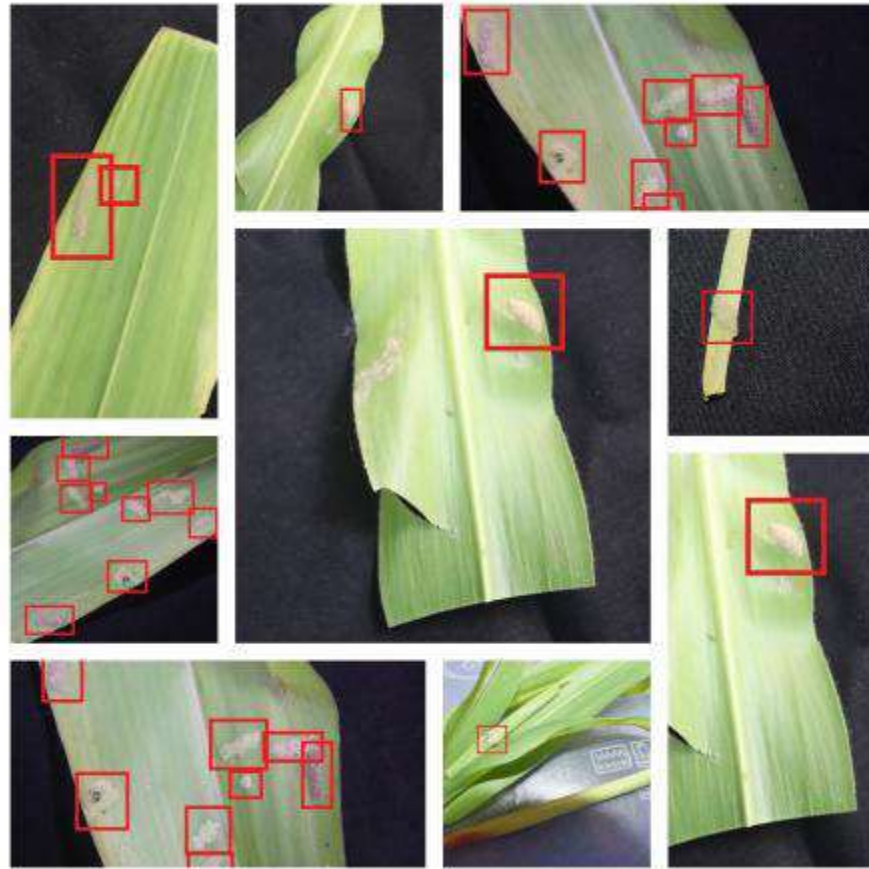
Fig2: Real time Module Side View



**Fig3: Front View**



### **Input Egg Mass**



**Fig4: Egg Mass Identification**

**Output: HSV Algorithm identifies Egg  
Mass**





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