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# Android Application for Automated Identification of Maize Fall Armyworm, Spodoptera frugiperda in India

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**Abstract- The identification of pests within the field is a significant challenge in the field of agriculture. It is essential to protect the crop by monitoring the pest thereby minimizing pesticides. Recently Fall Armyworm (FAW) is introduced to India and is now widespread throughout. It is one of the most dangerous pests, and it can wreck the maize field within a week. This work focuses on the automatic identification of Fall Armyworm (FAW) in larval stage using the android app. The user (farmer) can upload the pest image via an android application to the Anvil Cloud Service and uploaded image is processed in the Anvil Cloud. The processing uses Deep Learning technique called Convolution Neural Network (CNN). The result will be displayed on the android app. If the input image is predicted as FAW, the app provides remedial recommendations. We also performed the experiments to evaluate the accuracy of the deep learning model and obtained promising results for easy and quick identification of FAW, distinguishing from other closely related species and other maize infesting pests.**

***Keywords — Anvil Cloud, Convolution Neural Network, Deep Learning, Fall Armyworm (FAW), Digital Image Processing.***

## I. Introduction

Plant pests are a perplexity because they cause a significant reduction in the quantity and quality of agricultural production. They affect food crops, inflicting substantial losses to farmers, and threatening food security. The unfold of transboundary plant pests has enlarged dramatically in recent years. Economic process, trade, and temperature change and reduced resilience in production systems because of decades of agricultural intensification, have all compete for an area. Outbreaks and upsurges will cause massive losses to crops and pastures, threatening the livelihoods of vulnerable farmers and, therefore, the food and nutrition security of millions at a time. There is a need of multidisciplinary approach to tackle the farmer's problems.

Maize is an important cereal grain crop that was initially cultivated in American countries but now widely grown in India. Maize is cultivated throughout the country in diverse habitat. Karnataka is the leading producer contributing 13.70 percent of total countries production with the production of 3.73 MT and productivity of 2.90 MT per hector. However, various stress factors hindering the maize production, the insect pests are one among them. As many as 141 insect pests cause a varying degree of damage to maize crop right from sowing to till the harvest (Reddy and Trivedi, 2008). Today maize farmers struggle with unexpected precipitation patterns of weather, the horror of crop pests that may affect the quality and quantity of the harvest. One of the foremost dangerous pests is Fall Armyworm (FAW) which was introduced recently to India (Sharanabsappa et al., 2018), now widespread and causing severe loss in India and other Asian countries (Guo et al., 2018; Nagoshi et al, 2019, Wu et al., 2019; Mahadevaswamy et al., 2018). Initial identification and timely control measures are the basic prerequisite for successful management.

AI based pest diagnosis and decision support system has been used in developed countries. A study conducted regarding pest detection and extraction by using an image processing technique (Johnny et al., 2014) to detect insect pests in paddy field. The authors used background modelling to detect the presence of insect pests in the captured image, and using a median filter to remove the noise from the image captured. The authors have taken data from the paddy field. The results presented were promising however needed several improvements. Automated image capture and identification is not new, but in India, such studies and providing such decision support system is lacking. The current study focuses on the automatic

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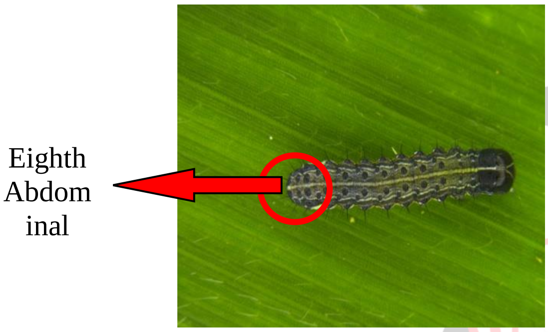
identification of FAW by using an android application. The farmer can uploads the image of the pest to the Anvil Cloud via the android app. The uploaded larval stage image gets pre-processed; the deep learning technique is applied and displays the relevant result on the android app.

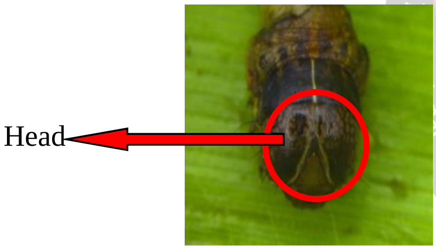
## II. METHODOLOGY

### A. *Image Acquisition*

In the maize fields, detection of FAW was carried out. Through Samsung A50 mobile camera images (data) of FAW are captured. The camera can capture images with 48-megapixel resolution. While grabbing image, attention is given to the head and 8th abdominal segment part, where white inverted 'Y' line on the head and four black dots in a square ('::') form on the 8th abdominal segment as shown in Fig. 1a and Fig. 1b. These two are the morphological characters which clearly distinguish from other related species.




**(a)**

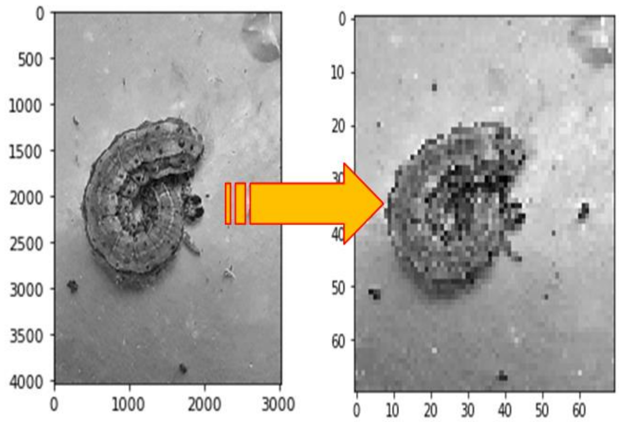



**(b)**

**Fig. 1 (a) Image of fall armyworm (FAW)**
**(b) Head of a of fall armyworm (FAW)**

The dataset contains around 1500 images of FAW, collected from UAHS, Shivamogga, Karnataka. One thousand images of non-FAW specimens (mainly maize pests such as Spodoptera liura, Helicoverpa armigera, Mythimna separata, Sesamia inferens and Chilo partellus) collected from different agricultural field and internet. Dataset is split into training and testing data, training has 80% of data to train the CNN model, and testing has 20% data to testing the CNN model. Training and testing process were made in the local machine, which had Intel i3 processor and 4GB RAM.

### B. *Pre-processing the Image*



**(a) (b)**

**Fig. 2. (a).Image captured from mobile (b)Resized image of FAW**

Usually, the image obtained from the mobile camera (Fig. 2a) is not suitable for the identification purpose because of various factors such as noise, lighting variations, image size issues, etc. To remove unwanted features in the images and also resize the image, pre-processing was done (Fig. 2b).

### C. *Detection of FAW in the image*

We know that machines recognize the image as a pixel. The algorithm used in this project is Convolution Neural Network (CNN). CNN algorithm is mainly divided into two parts i.e Feature Learning and Classification. The prominent role of the CNN algorithm is to extract the feature or scanning. It helps the machine to identify the image in the form of pixels and scan the image by using specific filters and store that information in the model.

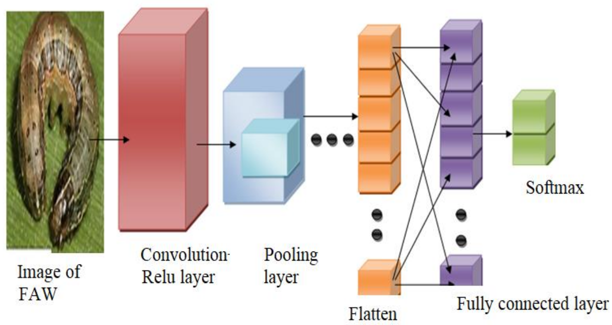



**Fig. 3. Convolution neural network (CNN) process architecture**

Fig. 3. represents the work flow of the CNN algorithm. CNN algorithm is mainly divided into two parts i.e Feature Learning and Classification.

#### Feature Learning

The feature learning includes the Convolution Layer, Relu Layer, and Pooling. Convolution layer is a layer where input is a pest image. It mainly contains three sets of filters, i.e. shape filter, colour filter, and edge filter. One by one, each filter is moved throughout the image. While moving the pixel value of the image is multiplied with a pixel value

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of the filter. Add them and divide them by the total number of pixels to get the output.

The Relu layer accepts the output of the Convolution layer as input. It is an Activation function, which means the Relu layer will only activate the node if the information is above a certain quantity. The primary function is to reduce overfitting.

$$f(x) = \begin{Bmatrix} 0 \text{ if } x < 0 \\ x \text{ if } x \geq 0 \end{Bmatrix} \qquad (1)$$

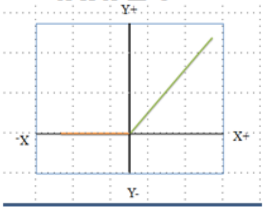


**Fig. 4. Relu graph representation**

Fig.4. and Equation (1) represent the Relu graph and Relu equation in which if ‘x’ value is greater than ‘0’or equal to ‘0’ then f(x) will be the same ‘x’ value. If ‘x’ values is less than ‘0’, then f(x) will be ‘0’.

Pooling takes the output of the Relu layer as input. The primary purpose is to reduce the size of the data. Data processing is high-speed due to the reduced size of data. It also reduces computational complexity and memory complexity.

### Classification

The classification includes Flatten, Fully Connected Layer, Softmax. Flatten accepts the Pooing layer's output as input and converts 'N' dimensional array into a '1' dimensional array. A fully connected layer connects to the output of flatten. Probability distribution algorithm used to calculate probability values. Softmax is a method used to calculate the highest probability.

### Anvil Cloud Architecture

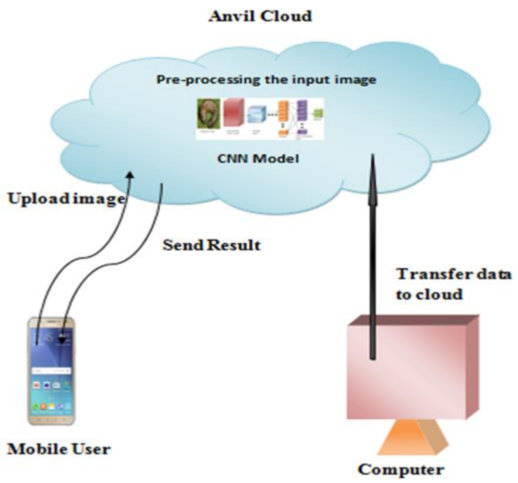


**Fig. 5. Anvil Cloud Architecture.**

The anvil cloud connects to a computer and user mobile as shown in Fig. 5. Computer stores CNN model and preprocessing code in the anvil cloud. Whenever a user(farmer) opens the application(app), it asks for upload the image of pest, anvil cloud receives the uploaded image, where image is preprocess and the CNN model is applied. Anvil cloud sends the result and displays on the screen of user mobile.


**Fig. 6. Icon of the android app.**

Anvil cloud provides a website link. Kodular platform converts website link into the android app. The Fig. 6. represents mobile application named “AGRO” used for automated identification of FAW.

### Functional Diagram of the System

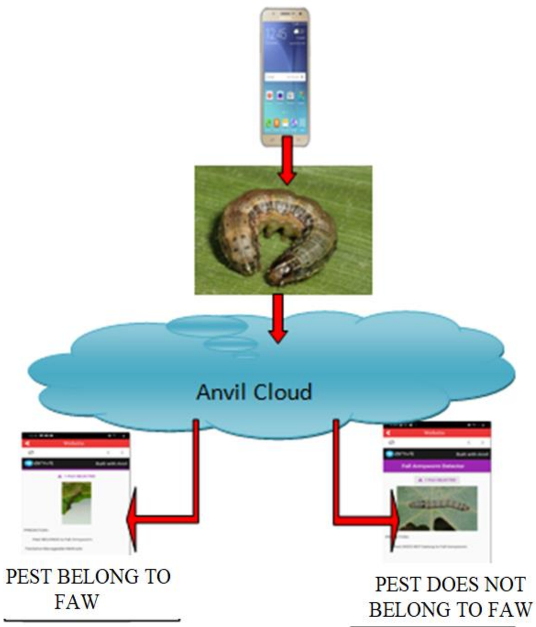


**Fig. 7. Functional Diagram of the Sytem**

Fig. 7. Shows the complete functional diagram of the system. The user (farmer) opens the application in the mobile and uploads the image of pest from files, gallery, or Google drive to Anvil Cloud. Pre-process the uploaded picture. Apply The CNN model to the pre-processed image. The final result is sent back and displayed on the mobile, along with the required remedies. Fig. 8. Represents accuracy graph. The blue colour line represents training accuracy, and the red colour line represents validation accuracy.


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**Training and Validation Accuracy Graph**

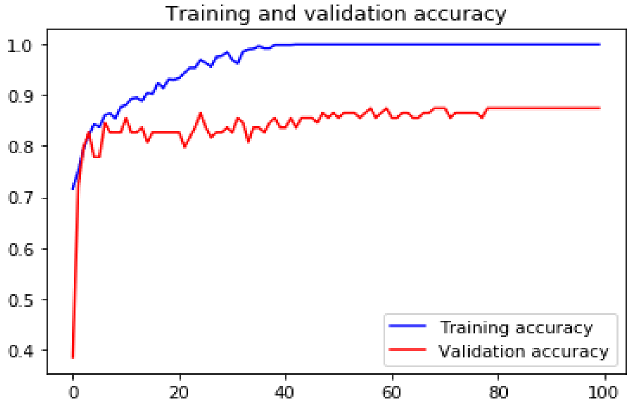


**Fig. 8. The graph of training and validation accuracy.**

## III. RESULTS AND DISCUSSION

Our study clearly demonstrated that mobile application developed for automatic identification of Fall Armyworm (FAW) using deep learning technique (CNN Algorithm) results with 90.7% of accuracy. The above screenshots represents detailed information regarding an android application. Whenever the user (farmer) clicks on a mobile application named ‘AGRO’ (Fig. 9a), the home page is displayed with ‘Upload’ button (Fig. 9b). Whenever user clicks on ‘Upload’ button, it shows various options like Gallery, Drives, Photos, Onedrive, Files etc. from where user can select the image of the larva and can upload (Fig. 9c). Once the image is uploaded, it displays the result on the android screen regarding whether the given picture of pest belongs to FAW or not. If result states as FAW, remedies are also provided as given by UAHS ad hoc recommendation (Fig. 9d). Else result states as pest does not belong to FAW (Fig. 9e).

Previously such AI based identification was done for FAW. Francis et al. (2019) developed a CNN model for automatic identification and classification of Fall Armyworm. The dataset is collected from the agriculture field, lab setup, crawling the internet, and data augmentation. Due to the lack of training datasets (60), prediction accuracy was very low-32%. However, our model identified 90.7% of accuracy

Simon et al. (2019) proposed machine learning algorithms in machine-driven identification and capturing of FAW moths within the field. They also used algorithms for automatic image capture and Identification of FAW Moths. Here, to collect moth images (data), Funnel pheromone traps, including raspberry PI, vision sensors, and motion sensors, are used. Collected information automatically sent to the cloud server for analysis. CNN based supervised machine learning is a technique used for classification.

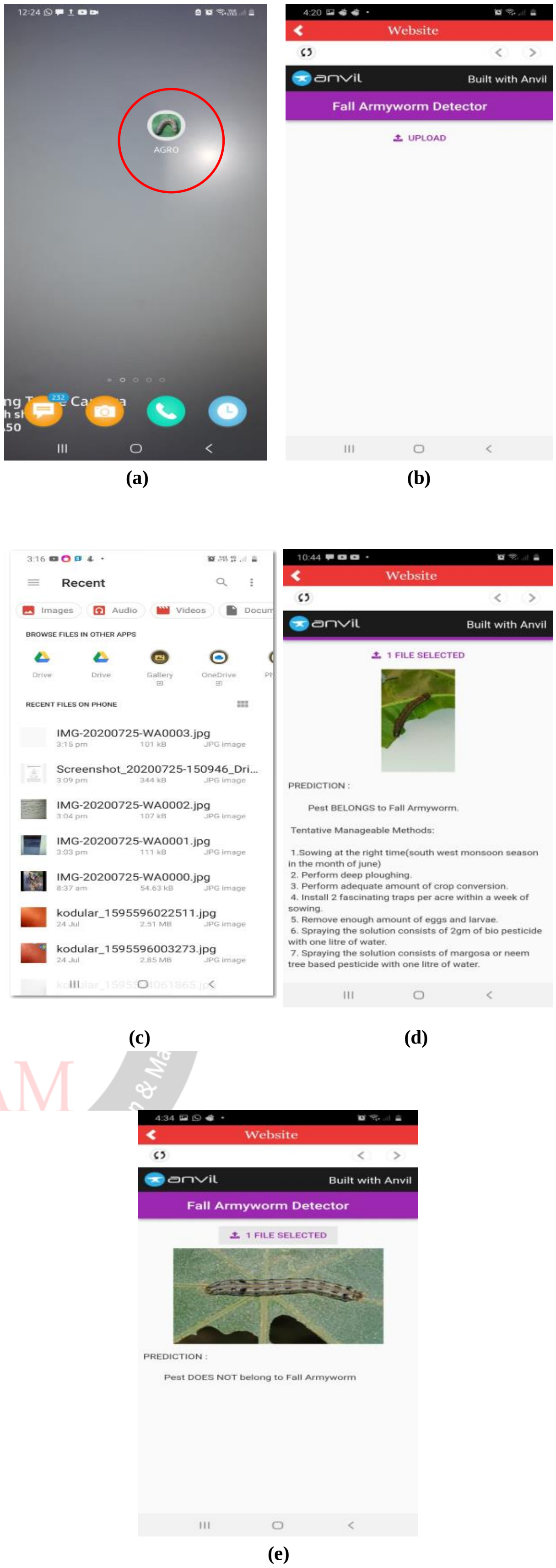


**Fig. 9. (a) Icon of the Android App (b) Home page of Android App. (c) Options that user can select to upload the image (d) Screen showing positive result. (e) Screen showing negative result.**

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In this android application, the user (farmer) can uploads the image of pest found in the agricultural field to Anvil Cloud and on the mobile screen, it displays the result. If the image identified as a Fall Armyworm, to overcome from the pest problem provides required remedies. Otherwise, app displays result as pest does not belong to Fall Armyworm. Hence, the app helpful for real time diagnosis and management practice to be initiated against FAW.

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