The Pharma Innovation Journal 2021; SP-10(10): 900-911

www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277- 7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2021; SP-10(10): 900-911

www.thepharmajournal.com
Received: 13-08-2021
Accepted: 23-09-2021

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An image repository of fall armyworm (FAW) with different severity level of infestation in maize

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Abstract
Fall armyworm has become a major concern for maize farmers in recent years, as it has resulted in significant yield losses in the maize field. A fall armyworm infestation might be detected automatically using a machine learning system, allowing for faster and accurate scouting of farmers' field operations. However, it is tedious for creating a machine-learning algorithm to discern between the target fall armyworm infestation and other sources of weeds, soil in a typical field. So, a vast amount of human-generated training data is required to train a machine learning system to consistently detect a specific fall armyworm infestation in the maize field. In this study, we created an image repository for different severity levels of fall armyworm infestation in maize. All of the high-quality photographs were shot with a digital camera against a variety of backgrounds with distinct light intensities in different locations. Visual scale ratings were also given to fall armyworm infestation in maize.

Keywords: Fall armyworm symptoms, image repository, maize fall armyworm, visual score rating

1. Introduction

The fall armyworm (*Spodoptera frugiperda*) is a noxious insect pest that belongs to the Noctuidae family and Lepidoptera order. Fall armyworm (FAW) is a sporadic pest in the United States since 1797. It is endemic to tropical and subtropical regions of America (CABI, 2017; FAO, 2017; Sparks, 1986; Hruska and Gould, 1997; Nagoshi, 2009) [7, 16, 40, 22, 31]. The fall armyworm was initially noticed as a prevalent maize pest in South and North America. It was first reported in Africa in 2016 (Sisay *et al.*, 2018) [38]. Before surfacing in 2018, it has spread to over 30 countries across tropical and southern Africa, including Madagascar, Seychelles, and Cabo Verde (Bateman *et al.*, 2018) [2]. It's a polyphagous pest (Baudron *et al.*, 2019) [3] that wreaks havoc on economically significant cultivated cereal crops like maize, rice, sorghum, cotton, and a variety of vegetable crops, posing a threat to food security (FAO, 2017; CABI, 2018; Bateman *et al.*, 2018) [16, 8, 2]. The fall armyworm feeds on a variety of plant parts, including leaves, stems, and reproductive organs (Tefera *et al.*, 2019) [39]. Walton and Luginbill (1916) [45] reported that there was a serious outbreak of FAW on corn and millets in 1912. Fall armyworm feeds primarily on young leaf whorls, ears, and tassels, grieving substantial damage to maize and leading to total yield loss on occasion (Sarmento *et al.*, 2002) [12].

Sharanabasappa and Kalleswaraswamy (2018) [38] reported that the emergence of this new invasive pest *Spodoptera frugiperda* was recorded for the first time on the Indian subcontinent in maize fields at the University of Agricultural and Horticultural Sciences, Shivamogga, Karnataka, on the 18th of May, 2018. Since its report from the state of Karnataka in May 2018, FAW has steadily expanded to several states and also documented the temporal spread of FAW inside India (Rakshit *et al.*, 2019) [34]. It spread to places like Bihar, Chhattisgarh, Gujarat, Maharashtra, Odisha, and West Bengal (CABI, 2020) [9]. The insect pest has also existed in Asian countries such as China, Japan, Bangladesh, Cambodia, Indonesia, Myanmar, Korea, Thailand, Sri Lanka, and Vietnam (FAO, 2019) [17].

The extensive use of smartphones among crop growers around the world, with an estimated 5 billion smartphones in use by 2020, has the potential to transform the smartphone into a useful tool for a wide range of food-growing groups (Hughes and Salathe, 2015) [23]. We have taken more than 11,000 high quality images on healthy and infested leaves of fall armyworm infestation with a digital camera and a smart-phone. Automatic diagnosis of plant diseases from captured images through computer vision and artificial intelligence research is feasible in technological advancements. In order to build a mobile application, it was more significant to apply new technology-oriented machine learning algorithms. Image data is a vital element in the development of machine learning and deep learning algorithms.

In this study, we have developed an image repository for the symptoms of fall armyworm infestation in the maize field. After that, scale ratings were assigned to all of the photographs of fall armyworm-infested maize leaves, cobs, and tassels.

2. Materials and Methods

2.1. Dataset collection

A large dataset was required to create an image repository of the maize fall armyworm infested leaves, cobs, tassels. Images with varied resolutions (android mobile phone, regular RGB camera); light conditions depending on the time of image capturing (e.g., illumination); and different seasons (e.g., temperature, humidity) were all part of our current data collection. We photographed the crop at various stages of development (i.e., vegetative and reproductive stages).

We took the photographs of fall armyworm infested maize plant parts with a Nikon D 7500 P - Digital Camera (Nikon F lens mount, 2.8 maximum aperture, Servo Auto Focus, Single Auto Focus autofocus, 3.15-inch screen size, touch screen, 23.5x15.6 mm sensor size, 20.9 Mega-pixels, 5568, 3712 px max resolution, CMOS sensor type, DX image sensor format) with camera mode set to auto and photos were taken under diverse ambient conditions at various time intervals for simplicity of usage. We purposely sought a variety of circumstances because the end-user (grower using a smartphone) may ultimately snap photographs under a variety of conditions. We took 4-7 photographs of each leaf with a standard point and shoot camera in automatic mode. As we photographed the leaf, it was turned 360 degrees. We found that this was critical since several photos allowed us to acquire additional data depending on the reflectance and the nature of the pest infestation. A total of more than 11000 photographs with varying severity levels of infestations were shot from FAW infested maize field to aid in the development of a system that uses CNNs (Convolutional Neural Network) to detect fall armyworm infection in maize fields in real-time and stored in the system (8 GB RAM; AMD Ryzen 5, 3500U with Radeon Vega Mobile Gfx 2.10 GHz) for image processing by following the methodology described by (Kulkarni, 2018; Militante, 2019; Syarief and Setiawan, 2020) [25, 30, 41].

The data records contain 11,251 images that depict 12 different classes of fall armyworm infestations in maize. The dataset contains images of healthy maize leaves (1000), pinhole caused by Fall armyworm (1963), the circular hole caused by FAW (2271), small to several lesions caused by FAW (3374), whorl leaf damage by FAW (1000), nil damage to slight damage at tips of the cobs (196), < 25% of cob area showing FAW infestation (384), 26 - 50% of cob area showing FAW infestation (151), 51 – 75% of cob area showing FAW infestation (124), > 75% of cob area showing FAW infestation (238), Healthy tassel (100), FAW infested tassel (459). The description and the total number of image datasets were summarized in table 1.

Photos were shot from various blocks of Tiruvannamalai districts (Perunthuraipattu, Thenmudiyanur, Agarampalipattu, Allapanur, Rayandapuram, Kankayanur, Varakur and Perumanam), Thoothukudi districts (Killikulam) of Tamil Nadu and various maize growing research plots of Tamil Nadu Agricultural University (Eastern Block, field no: 36, behind the administrative building, TNAU and eastern block, near red fort hostel, TNAU, Coimbatore). Then the collected images were stored in the system for further image processing analysis.

2.2. Visual scale ratings for maize leaves, cobs and tassels

The collected images were labelled based on visual rating scales for leaf damage categorization. The categorization of images was done as per the scale (1-5 scale) proposed by (Cruz and Turpin 1983; Figueiredo *et al.*, 2006; Pogetto *et al.*, 2012; Grijalba *et al.*, 2018; Kuate *et al.*, 2019; Santo *et al.*, 2020) [10, 18, 11, 21, 19, 14], 0-9 scale (Wiseman *et al.*, 1996; Davis *et al.*, 1996; Williams *et al.*, 1999; Lynch *et al.*, 1999a, 1999b; Rea *et al.*, 2000, 2002; Buntin *et al.*, 2001, 2004, Buntin, 2008; Michelotto *et al.*, 2017) [47, 46, 26, 35, 6, 5, 8, 28], a novel scale (0-4) proposed by (Toepfer *et al.*, 2021) [43] and TNAU unpublished protocol (1-5 scale) for maize fall armyworm infested leaves. Maize fall armyworm infested cobs were labelled as per the scale (0-9) proposed by Prasanna *et al.* (2018) [33] and TNAU Unpublished protocol (1-5 scale). Then the maize tassels were also classified as healthier and fall armyworm infested tassels.

2.3. Classification used for the development of model

In the instance of fall armyworm infestation in maize leaves, the reviewed scale ratings were not appeared to be discrete, so new scale ratings were employed to create a model. The image dataset used for developing the model is illustrated in Fig.1. The newly proposed leaf classification includes healthy maize leaves (1a), pinhole symptoms (1b), circular hole symptoms (1c), ragged hole symptoms (1d) and whorl leaf damage symptoms (1e). The cob per cent damage classification includes nil damage to slight damage at tip of the cob (1f), < 25% of cob area showing FAW infestation (1g), 26 - 50% of cob area showing FAW infestation (1h), 51 – 75% of cob area showing FAW infestation (1i), > 75% of cob area showing FAW infestation (1j). The tassel damage classification includes healthy tassel (1k), FAW infested tassel (1l). The whole image dataset of fall armyworm infested leaves was illustrated in Fig. 8-12. The scale ratings proposed by TNAU were assigned to the cob damage (Fig.13-17). The tassels were classified as healthier and infested (Fig. 18-19). These labelled photos will be proved useful in the development of revolutionary computer vision and deep learning technologies in agriculture.

3. Results and Discussion

3.1. Image repository

We developed an image repository (>11,000 images) for fall armyworm infested maize leaves, cobs and tassels. In addition, an image library was built to store all the image repositories in the cloud for future machine learning algorithm development.

We weren't only restricted to Coimbatore to document the fall armyworm infestation in maize. We also visited the districts of Tiruvannamalai and Thoothukudi, as we needed to cover a broad geographic area where the infestation had been photographed.

In order to achieve a high level of accuracy in the machine and deep learning model development, ample image datasets were acquired. If we feed a computer a small number of image datasets, the machine will not learn enough level of certainty to predict properly, and it will occasionally make errors. It will accurately identify the fall armyworm infested maize dataset when we offer a huge image dataset. Data augmentation is also done while doing the image processing to augment the photographs. As a result, the dataset will expand, with the system's python code performing the heavy lifting. There was a vast image dataset obtained via data augmentation at the end of the image processing stage to create the machine learning model The present findings on image repository of fall armyworm infestation in maize were similar to the findings on the image repository of maize northern leaf blight.

3.2. Visual scale ratings for damage assessment

The "yes–no damage scale" notes whether maize plant has been infested by the fall armyworm, regardless of the severity of the damage (Gómez *et al.*, 2013; Cancino *et al.*, 2016; Midega *et al.*, 2018; Aguirre *et al.*, 2019; FAO and CABI, 2019; Barrios *et al.*, 2019; Maruthadurai and Ramesh, 2020) [20, 13, 29, 1, 15, 24, 27]. It wasn't appropriate in many cases because it didn't provide information on the extent of the damage. The current findings on score ratings (1-5) for maize fall armyworm-infested photos (Fig.2) were similar to those described in the "simple 1 to 5 whole plant damage scale for fall armyworm" (Table 2) (Cruz and Turpin 1983; Figueiredo *et al.*, 2006; Pogetto *et al.*, 2012; Grijalba *et al.*, 2018; Kuate *et al.*, 2019; Santo *et al.*, 2020) [10, 18, 11, 21, 19, 14]. Because fine changes between damage levels cannot be recognised, and human bias may influence the results due to differing judgments on what little, medium and major damage means, this scale has been abandoned for practical use. The findings on score ratings (0-9) for fall armyworm infestation in maize leaves (Fig.3) were seemed to be similar to the ordinal data type "Davis' 0 to 9 whorl & furl damage scale for fall armyworm" (Table 3). It has been historically adapted to be the most widely used leaf damage scale for the fall armyworm (Wiseman *et al.*, 1996; Davis *et al.*, 1996; Williams *et al.*, 1999; Lynch *et al.*, 1999a, 1999b; Rea *et al.*, 2000, 2002; Buntin *et al.*, 2001, 2004, Buntin, 2008; Michelotto *et al.*, 2017; Prasanna *et al.*, 2018) [47, 46, 26, 35, 6, 5, 8, 28, 33]. Human bias could affect the results, particularly between scores 5 and 7, due to the scale's exceedingly complex, inconsistently presented rating levels between the scores and thus variously interpretable descriptive components. The present findings on score ratings (0-4) (Fig.4) for leaf damage index were similar to those described by (Toepfer *et al.*, 2021) [43] (Table 4). However, there were no discrete between 3 and 4 scales. The findings on score ratings (1-5) for leaf damage assessment (Fig.5) were similar to those described in the "Visual rating scale for whorl leaf damage" (Table 5) (TNAU unpublished protocol).

Score ratings (1-9) for cob damage infestation (Fig.6) were similar to those described in the visual rating scale for cob damage" (Table 6) (Prasanna *et al.*, 2018) [33]. The present findings on score ratings (1-5) for cob damage assessment (Fig.7) were similar to those described in the "Visual rating scale based on per cent cob infestation" (Table 7) (TNAU unpublished protocol).

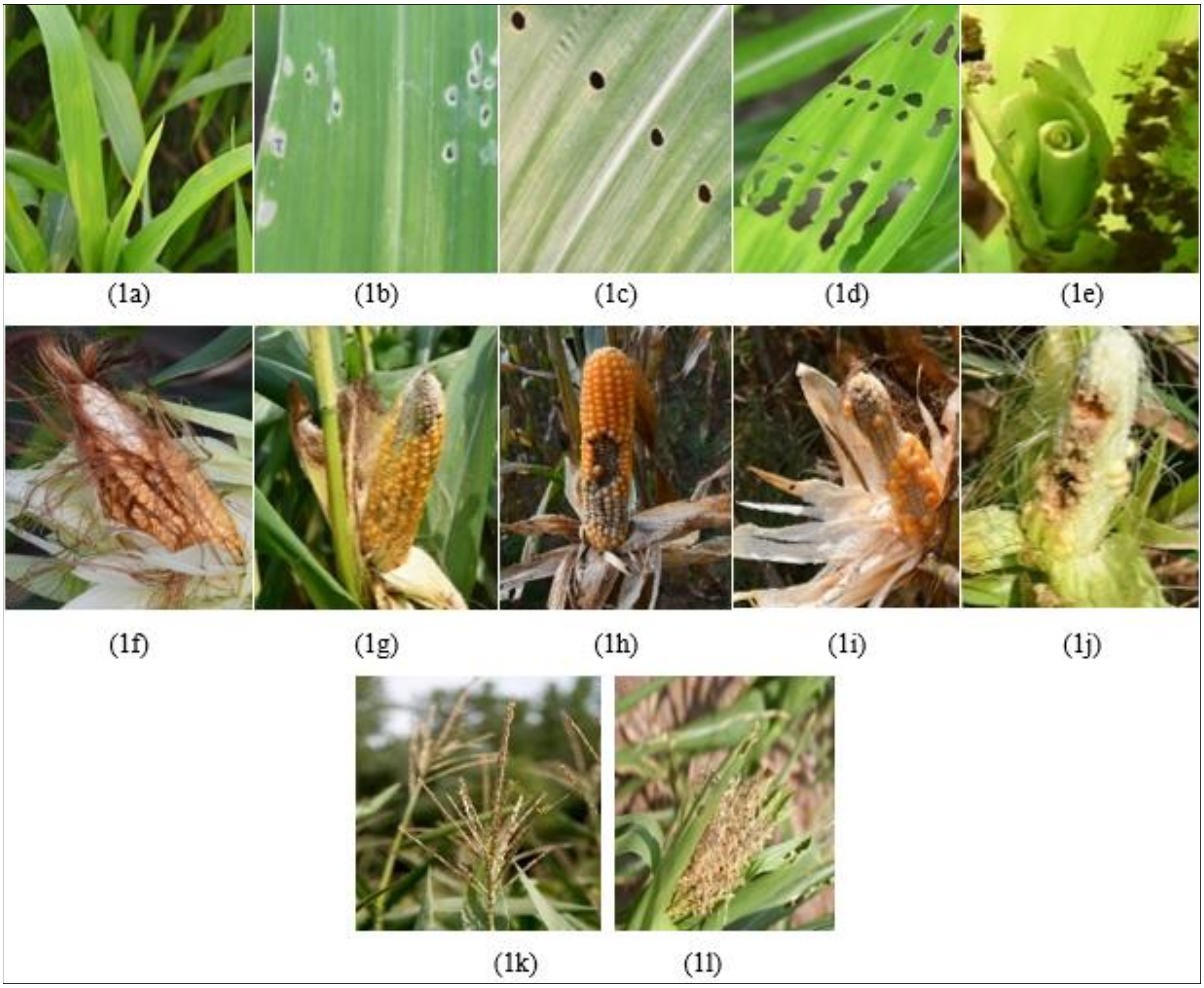

Fig 1: The image dataset used for model development

Table 1: Description and total number of the image dataset

Maize Leaves	
Classes	**Number of photos taken**
Healthy leaves	1000
Pinhole caused by FAW	1963
Circular hole caused by FAW	2271
Small to several lesions caused by FAW	3374
Whorl leaf is eaten by FAW	1000
Maize cob	
Classes	Number of photos taken
Nil damage to slight damage at tips of the cobs	196
< 25% of cob area showing FAW infestation	384
26 - 50% of cob area showing FAW infestation	151
51 – 75% of cob area showing FAW infestation	124
> 75% of cob area showing FAW infestation	238
Maize tassel	
Classes	Number of photos taken
Healthy tassel	100
FAW infested tassel	459

Table 2: Simple 1 - 5 whole plant damage score for the fall armyworm (Cruz and Turpin, 1983) [10]

Score	Simple 1 to 5 whole plant damage scale for the fall armyworm (whole plant assessed)
1	No damage
2	Little damage
3	Medium damage
4	Heavy damage (most of the plant with damage symptoms
5	Very heavy or total damage (plant is almost dying)

Fig 2: Simple 1 - 5 whole plant damage score for the fall armyworm

Table 3: Visual rating scale based on leaf damage (Davis *et al.*, 1992)

Scale	Description
0	No visible leaf-feeding damage
1	Few pinholes on 1-2 older leaves
2	Several shot-hole injuries on a few leaves (<5 leaves) and small circular hole damage to leaves
3	Several shot-hole injuries on several leaves (6–8 leaves) or small lesions/pinholes, small circular lesions, and a few small elongated (rectangular-shaped) lesions of up to 1.3 cm in length present on whorl and furl leaves
4	Elongated lesions (>2.5 cm long) on 8-10 leaves, plus a few small- to mid-sized uniform to irregular-shaped holes (basement membrane consumed) eaten from the whorl and/or furl leaves
5	Several large elongated lesions present on several whorls and furl leaves and/or several large uniforms to irregular-shaped holes eaten from furl and whorl leaves
6	Many elongated lesions of all sizes present on several whorls and furl leaves plus several large uniform to irregular-shaped holes eaten from the whorl and furl leaves
7	Many elongated lesions of all sizes present on most whorl and furl leaves plus many mid to large-sized uniform to irregular-shaped holes eaten from the whorl and furl leaves
8	Whorl and furl leaves almost totally destroyed and plant dying as a result of extensive foliar damage
9	The whorl almost or completely eaten away and several lesions with more areas dying

Fig 3: Visual rating scale based on leaf damage

Table 4: Novel scale ratings for leaf damage index (Toepfer *et al.*, 2021) [43]

Score	Description
0	No damage
1	Little damage (pinholes, and/or small holes, small leaf edge parts eaten, shot holes)
2	Medium damage (some larger holes and/or larger leaf edge areas eaten)
3	Heavy damage (many larger holes and/or larger leaf edge areas eaten
4	Total damage (destroyed, non-functional leaves)

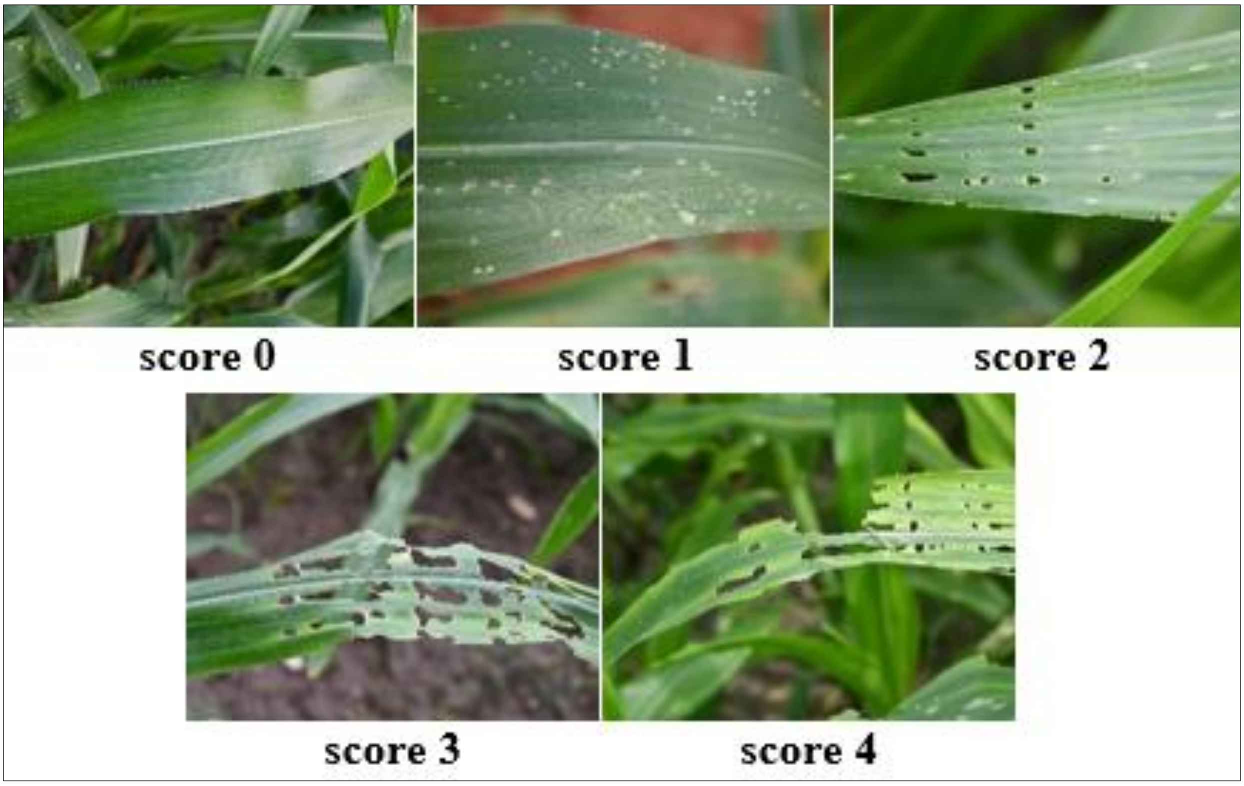

Fig 4: Novel scale ratings for leaf damage index

Table 5: Visual scale ratings based on whorl damage (TNAU unpublished protocol)

Scale	Description
1	Nil damage to pinhole damage
2	Circular/ elongated holes less than 1 inch on whorl leaves
3	Elongated holes > 1inch on whorl leaves without shredding
4	Elongated holes with mild shredding on whorl leaves
5	Severe shredding and defoliation of whorl and furl leaves

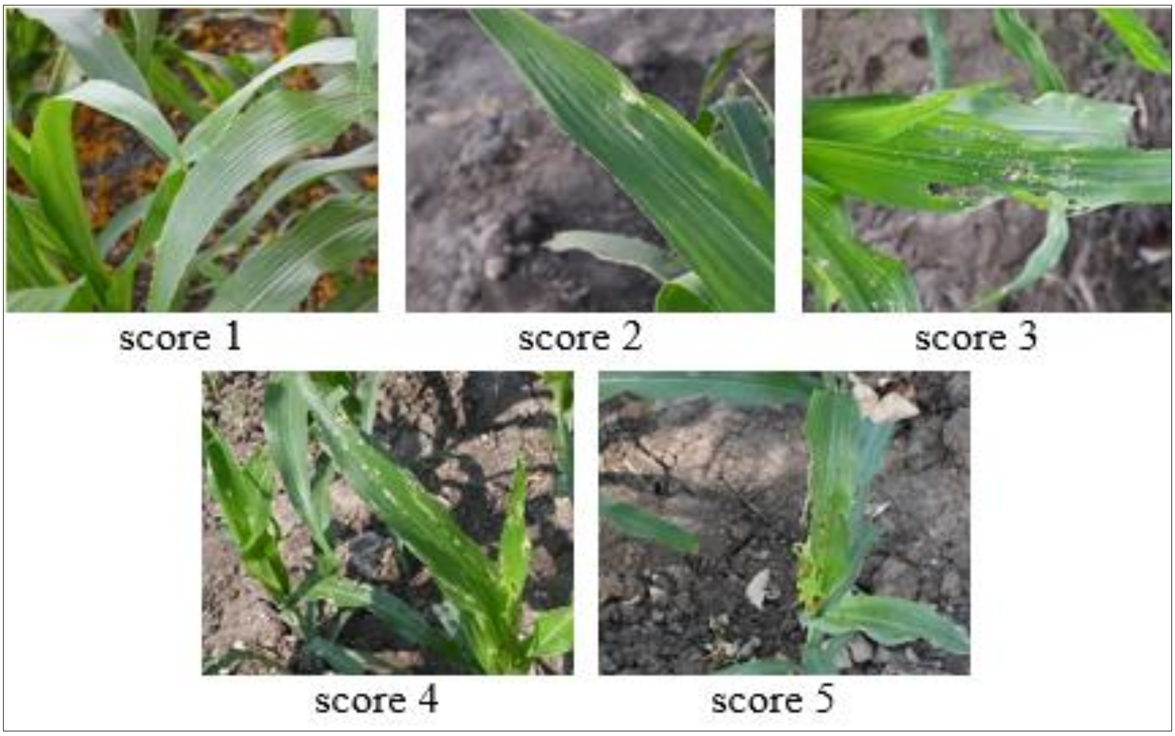

Fig 5: Visual scale ratings based on whorl damage

Table 6: Visual rating scale based on ear damage (Prasanna *et al.*, 2018) [33]

Scale	Description
1	No damage to the ear
2	Damage to a few kernels (<5) or less than 5% damage to an ear
3	Damage to a few kernels (6-15) or less than 10% damage to an ear
4	Damage to 16-30 kernels or less than 15% damage to an ear
5	Damage to 31-50 kernels or less than 25% damage to an ear
6	Damage to 51-75 kernels or more than 35% but less than 50% damage to an ear
7	Damage to 76-100 kernels or more than 50% but less than 60% damage to an ear
8	Damage to > 100% kernels or more than 60% but less than 100% damage to an ear
9	Almost 100% damage to an ear

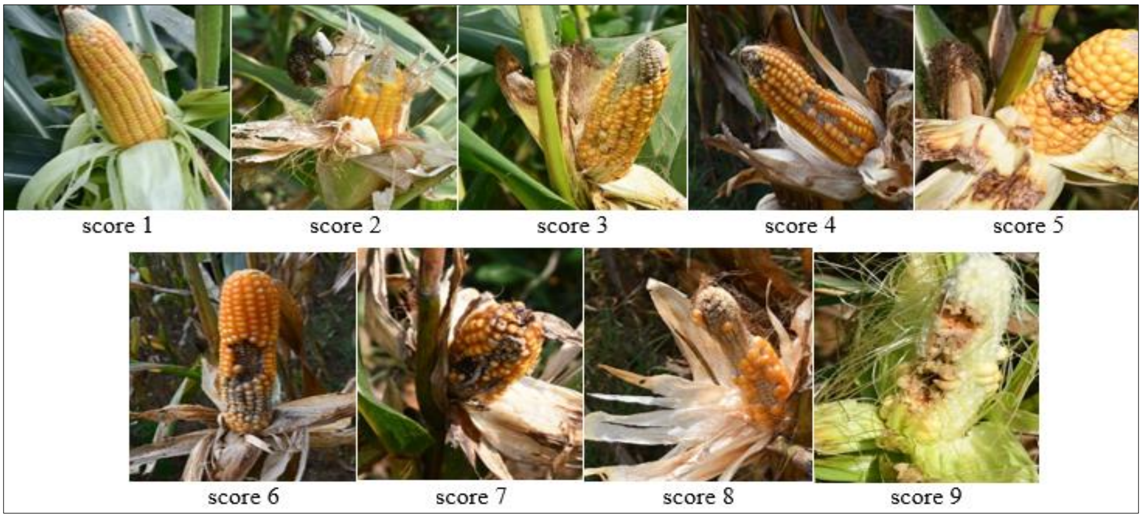

Fig 6: Visual rating scale based on ear damage

Table 7: Visual score ratings based on per cent cob infestation (TNAU unpublished protocol)

Scale	Description
1	Nil damage to slight damage at tips of the cobs
2	< 25% of cob area showing FAW infestation
3	26 - 50% of cob area showing FAW infestation
4	51 – 75% of cob area showing FAW infestation
5	> 75% of cob area showing FAW infestation

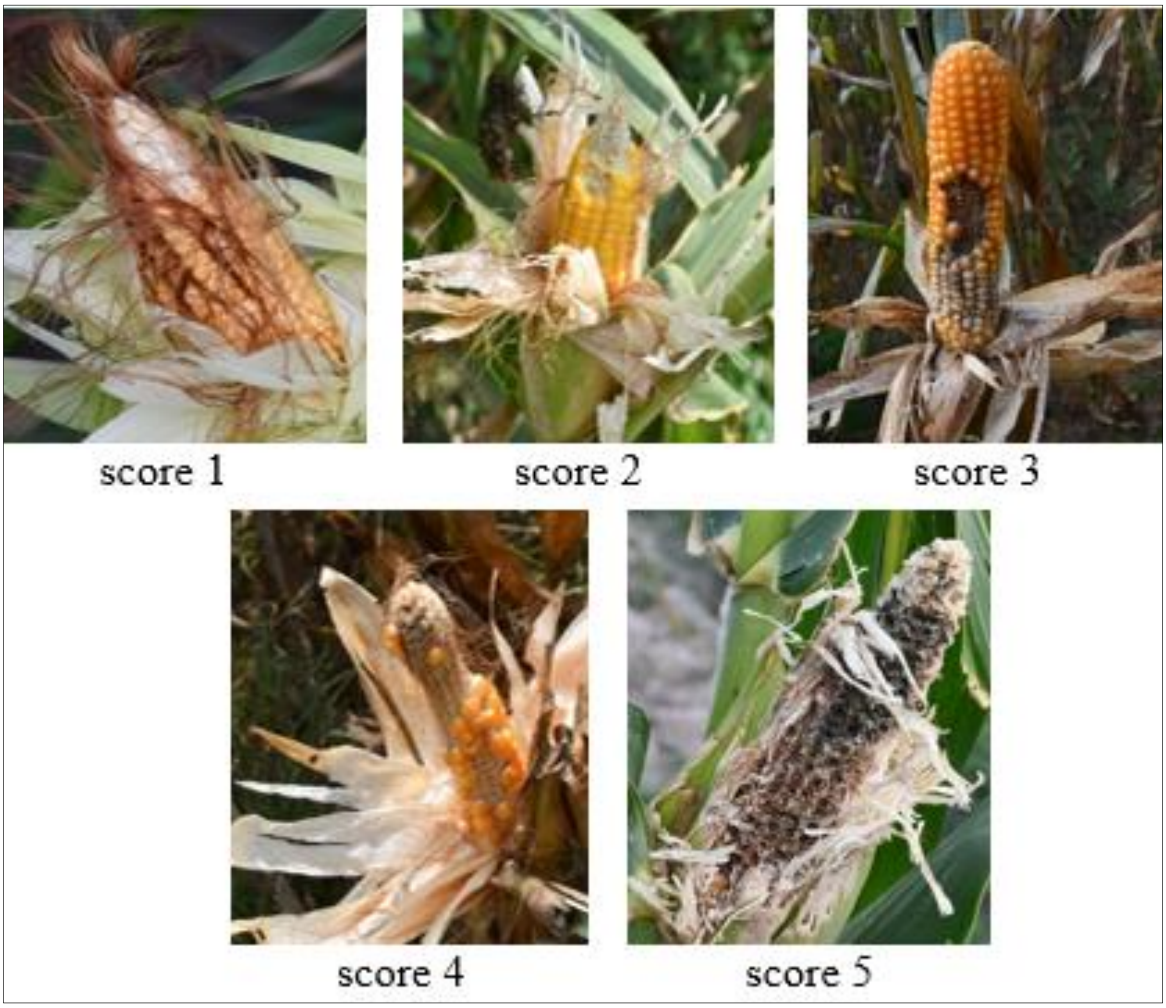

Fig 7: Visual score ratings based on per cent cob infestation (TNAU unpublished protocol)

Fig 8: Healthy maize leaves

Fig 9: Pinhole symptom caused by fall armyworm

Fig 10: Circular hole symptom caused by fall armyworm

Fig 11: Ragged hole symptom caused by fall armyworm

Fig 12: Whorl leaf damage caused by fall armyworm

Fig 13: Nil damage to slight damage at tip of the cob

Fig 14: < 25% of cob area showing fall armyworm infestation

Fig 15: 25 – 50% of cob area showing fall armyworm infestation

Fig 16: 51-75% of cob area showing fall armyworm infestation

Fig 17: >75% of cob area showing fall armyworm infestation

Fig 18: Healthy maize tassel

Fig 19: Fall armyworm infested maize tassel

4. Conclusion

We developed an image repository for fall armyworm infestation in maize. It can be useful for the development of deep learning models and app development. More fall armyworm infested datasets will be included in future work in order to strengthen the image dataset. It is possible to create a mobile application and make it freely available on Google Play.

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