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Application of TensorFlow model for identification of herbaceous mimosa (*Mimosa strigillosa*) from digital images

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ABSTRACT

This study explored the use of TensorFlow image recognition model to identify herbaceous mimosa (*Mimosa strigillosa*) from digital images. There is a demand for such technology toward digital mapping of the spatial distribution of these important perennial legumes in the context of pasture management and as well as management of reclamation ground cover landscapes. This study provided evidence of successful application of TensorFlow model for identification of herbaceous mimosa from digital images with final accuracy of 95 % or more. The complexity of ground images of multiple objects in this study is suspected to induce fluctuations in validation accuracy. Such fluctuation of the validation accuracy, however, was shown to decline over time as the accuracy increased with more processing epochs involved. Despite the downside of intensive data preparation and heavy computing resources, the approach tested in this study is promising toward the next step of the technology application for identification of herbaceous mimosa patches from images acquired using Unmanned Aerial Vehicle (UAV).

1. Introduction

Herbaceous mimosa (*Mimosa strigillosa* Torr. & A. Gray [Fabaceae]), a perennial warm-season nitrogen fixing legume native to the Southern United States (Fig. 1), is an ideal climate smart species to promote resilient landscapes and sustainable agricultural systems due to its ability to withstand drought conditions [1] and its ability to help control soil erosion due to its rapid spread, mat-like growth habit, and deep root system [2]. This legume is especially suitable for pastures due to its high crude protein content and high palatability for grazing beef cattle [3]. In addition to excellent grazing tolerance and quality, it can contribute to ecosystem services by enhancing habitat for wildlife and pollinators [3,4,5].

The native range of herbaceous mimosa, also known as Sunshine mimosa or powderpuff is shown in Fig. 1 based on data from United States Department of Agriculture (USDA) Natural Resource Conservation Service (NRC) [6]. The range of herbaceous mimosa includes southeastern counties in Texas, almost all parishes in Louisiana, southern counties in Arkansas, a few western counties in Mississippi (those within the Mississippi river valley), a few southern counties in Georgia and most counties in Florida. According to the database managed by Global Biodiversity Information Facility (GBIF) the reported occurrences of this species are beyond its reported native range (Fig. 1) [7]. The computer vision model managed by iNaturalist [8] recognizes herbaceous mimosa taxon and therefore large-scale geo-predictions have been made available (Fig. 2).

Geographic distribution maps of herbaceous mimosa can be useful for large-scale studies such as evaluations of the impact of wide-spread drought and/or wildfire on this species distributions and assessment of climate change impact on the geographic dynamic of this species. At farm level scale, however, this large-scale information will not be useful. The use of artificial intelligence technology toward high fidelity mapping of herbaceous mimosa at the farm scale may be possible based on the research reports involving other plant species [9,10,11]. An important key technology toward this goal is a machine vision piece for identification of the species from digital imageries. Reliable detection of the species from digital images is an important requirement for scaling up the approach to use aerial Unmanned Aerial Vehicle (UAV) data. The

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resulting high-resolution spatial distribution map of herbaceous mimosa can be overlaid with microclimate, soil, elevation, land management practices, farm vehicle traffic, animal grazing, and other relevant information to enrich our understanding of how these factors influence the ecophysiology of this species across the study area.

Artificial neural network evaluation was inspired by studies about the central nervous systems of mammals involving interconnected neurons organized in layers. The approach started with a two-layer network model called perceptron [12] and received a breakthrough with the fast-learning algorithms in mid-2000s [13]. and lately gaining fast advancements due to acceleration in computer hardware technology. The use of 3–5 layers of network training (neurons) in around the year 2012 was considered deep learning, while in 2017 use of at least 100–200 layers was considered as deep learning [14]. The learning via progressive abstraction resembles vision biology in the human brain. The human visual system is indeed organized into different layers with different roles such as visual cortex V1 (consisting of 140 neurons) in the lower posterior part of the brain with dedicated functions for discriminating basic properties and small change in visual orientation, spatial frequencies, and colors. The V1 is then connected to V2, V3, V4, V5, and V6, doing progressively more complex image processing and recognition of more sophisticated concepts such as shapes, faces, animals, and other advanced recognition tasks. Deep learning has taken inspiration from this layer-based organization of the human visual system with surface neuron layers handling basic image properties while the deep layers take care of more sophisticated properties [14].

The objective of this study is to evaluate the performance of an open-source TensorFlow deep learning model [15] for recognition of herbaceous mimosa from digital photography data collected from two geographies in Louisiana, USA.

2. Materials and methods

2.1. Study sites descriptions

The orthomosaic aerial maps for the study locations in Bossier and Assumption parishes, Louisiana, USA are shown in Fig. 3. Digital image data collection at the Bossier parish site involved approximately 17,000 m^2 area as part of a pasture field within the LSU AgCenter Red River Research Station in Bossier City, LA. In Assumption Parish, LA digital images collection involved 4000 m^2 area consisting of a long strip of farm access dirt road in sugarcane fields in Napoleonville, LA. Therefore, the herbaceous mimosa in this study were observed with the different background of either pasture or naturally existing vegetation along a farm access road.

2.2. Data collections and preparations

Image data of herbaceous mimosa and other land cover were taken using Olympus TG6 GPS camera (Olympus Corporation, Tokyo, Japan). The handheld digital camera was installed on a monopod to capture nadir (vertical downward) photos at approximately 1.2 m above ground. The camera was controlled remotely with Android app OI share installed on Nautiz X6 (Handheld Group AB, Lidkoping, Sweden) device through Wi-Fi connection. The aerial maps in Section 2.1 were generated based on data acquired using DJI Matrice 300 RTK quadcopter UAV mounted with either DJI H_2O sensor (Napoleonville location) or MicaSense RedEdge-MX Multispectral sensor (Bossier City location). Individual digital images of mimosa and non-mimosa plants from the study locations with the original resolution of 4000 × 3000 pixels were split into 12 pieces by dividing 3 divisions vertically and 4 divisions horizontally. This approach was taken to increase the amount of data required for the machine learning algorithm. The resulting individual images were assigned with a unique filename containing quadrant information related to the original image. For example, image file P63008350203.jpg is the 2nd vertical section and 3rd horizontal section of image P6300835.jpg. Examples of imagery input data are shown in Fig. 4. Handheld digital image data were used for TensorFlow-based plant identification of mimosa plants whereas UAV image data were used for the map describing the study area (Fig. 3).

The following rules were used when annotated image input data as mimosa plants versus other ground covers. For image annotated as mimosa, 25 % of the image must contain mimosa plants and not more than 15 % of other plants should be in the image (Fig. 5a, 5b, and 5c).

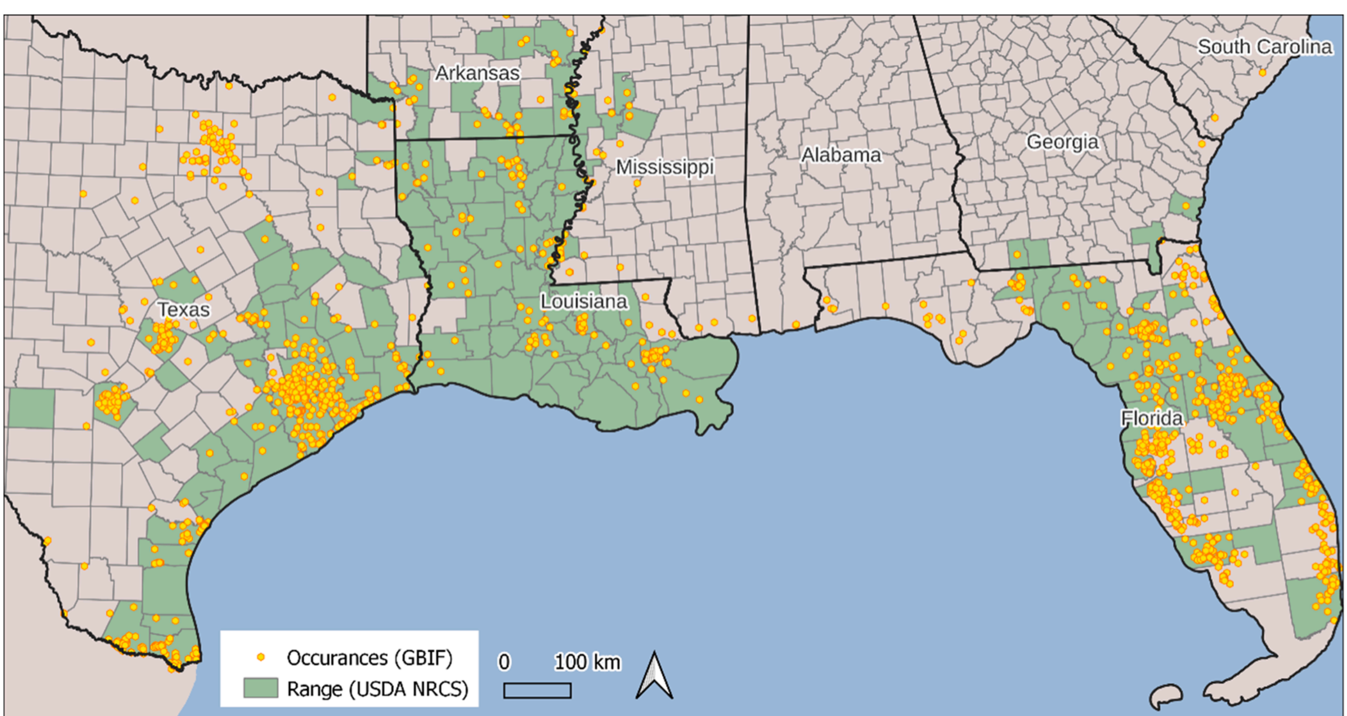

Fig. 1. The native range [4] and reported occurrences [5] of herbaceous mimosa (*Mimosa strigillosa*).

For other ground covers, mimosa plants should be completely absent in the image, and it can contain any mixture of plants and other surface background (Fig. 5d, 5e, and 5f).

2.3. Model descriptions

The model was written in python programming language in Jupyter Notebook interface environment with TensorFlow library installed in virtual environment. To accommodate streamlining continuous tensor (matrix of matrixed) of the convolutional neurol network (CNN) of the dimension of input images were first standardized to the same size of 180 × 180 pixels (Table 1). In the next step, the input data were split with 80 % of datasets for training and the remaining 20 % for validation. The TensorFlow model was run with 2116, 1678, 842, 422, 168, 154, and 134 total number of images with the corresponding number of images for validation as follows: 424, 326, 168, 84, 34, and 30. Such exercise of running the model with varying input size is to evaluate the resulting accuracy and processing duration with AMD Ryzen 5 Windows PC with 16 GB RAM. The batch for training was set to 10 (Table 1). This is the value of the hyperparameter of gradient descent controlling the number of training samples to work through before the model internal parameters are updated. The training and validation accuracy assessments were conducted for each of the total 250 epochs. To avoid overfitting images, inputs were augmented by randomly rotating them. A kernel of 3 × 3 was used to perform convolution of the image data using 128 neuron layers (Table 1). Rectified Linear Unit (RELU) activation function was used to convert complex input data into a value between 0 and 1 within each neuron. Once the convolution operation was done, the layers were flattened to input the data into the neural network. The drop out of 0.5 was used, meaning 50 % of the layer outputs were randomly ignored to prevent overfitting. On the final node of the CNN, a more sophisticated sigmoid activation function was applied to assign the output value of 0 for images identified as non-herbaceous mimosa and 1 for images identified as herbaceous mimosa.

3. Results

TensorFlow performances in terms of loss values and validation accuracy for discriminating mimosa versus other ground covers under different input sizes are shown in Fig. 6. Results of running the TensorFlow model with total images of 422 (84 validation images) or less are characterized by high degree of fluctuating accuracy (between 0.55 and 0.87) even toward the 250 final epochs and with relatively high and fluctuating loss values (Fig. 6a to 6d). Validation accuracy was relatively stable at 0.75 or higher after about 210 epochs when the TensorFlow model was run with the total number of images of 842, 1678, and 2116 (validation images of 57, 225, 424) with (Fig. 6e to 6g). The most satisfactory results in term of validation accuracy and stability toward the last 40 epochs or so were demonstrated by the two scenarios with the greatest number of images of 1678 and 2116 (validation images of 225 and 424). These scenarios were the only cases with a consistent decreasing trend of loss values (Fig. 6f and 6g).

The tradeoff between resulting mimosa identification validation accuracy and processing duration is shown in Fig. 7. Whereas validation accuracy shows hyperbolic trend with increasing number of input images used in the model, processing duration shows slightly more linear trend as number of input images increases (with slight upward curvature). Ligand binding function explains the relationship between validation accuracy and total number of images used in the model with r^2 of 0.9792 whereas quadratic equation describes processing duration as function of total number of images used in the model with r^2 of 0.9985. Based on this exercise, a reasonable accuracy of 0.95 or higher can be expected when TensorFlow model in this study is provided with 842 total input images (168 validation images) with the minimum processing time of 7.3 h. A random test involving the final Keras models suggested reliable performance of these models in accurately distinguishing herbaceous mimosa from other ground cover images.

4. Discussion

The satisfactory results of the TensorFlow approach to identify herbaceous mimosa from digital imagery requires large amount of input images with a distinct tradeoff between accuracy and length of processing. Greater number of input images also means a more intensive data collection and preparation. It is expected, however, that the developed model can be applied with the expectation to perform robustly against new datasets. This expectation is rooted from the fact that the validation performance of the model tested was very good despite the very different nature of herbaceous mimosa in the two study locations (planted pasture versus natural occurring population). To our knowledge, the complexity of the image dataset used in this TensorFlow image detection study is much higher than the typical example of this

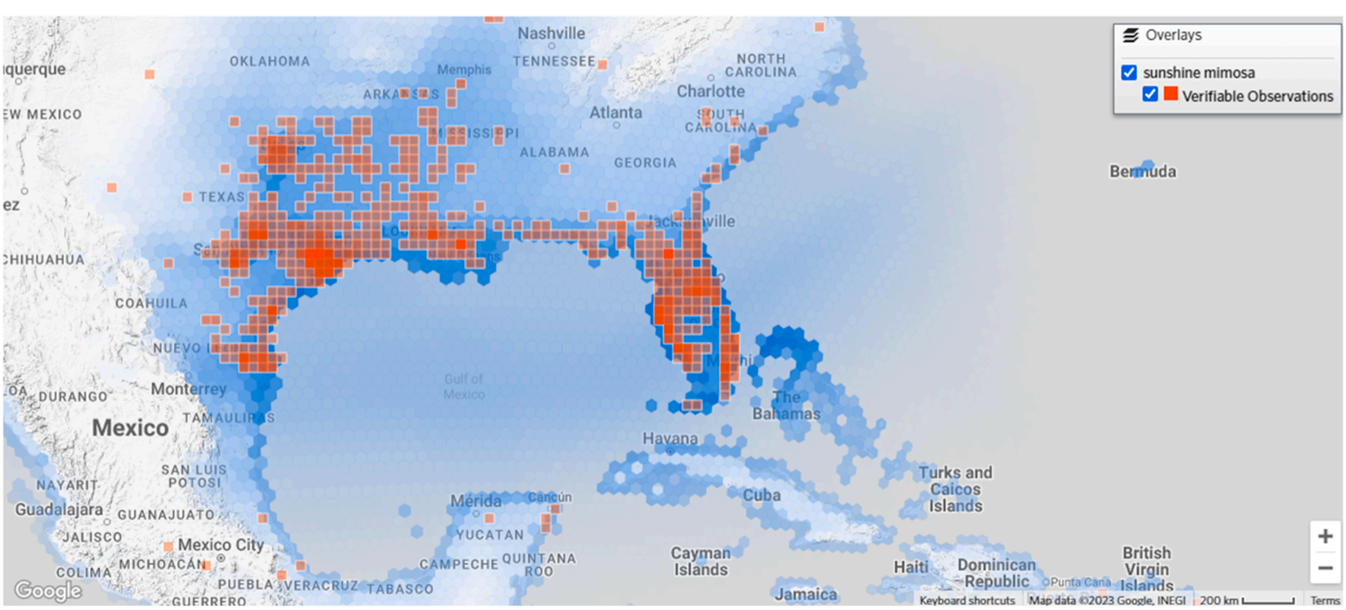

Fig. 2. Large scale prediction of spatial distribution of herbaceous mimosa [8].

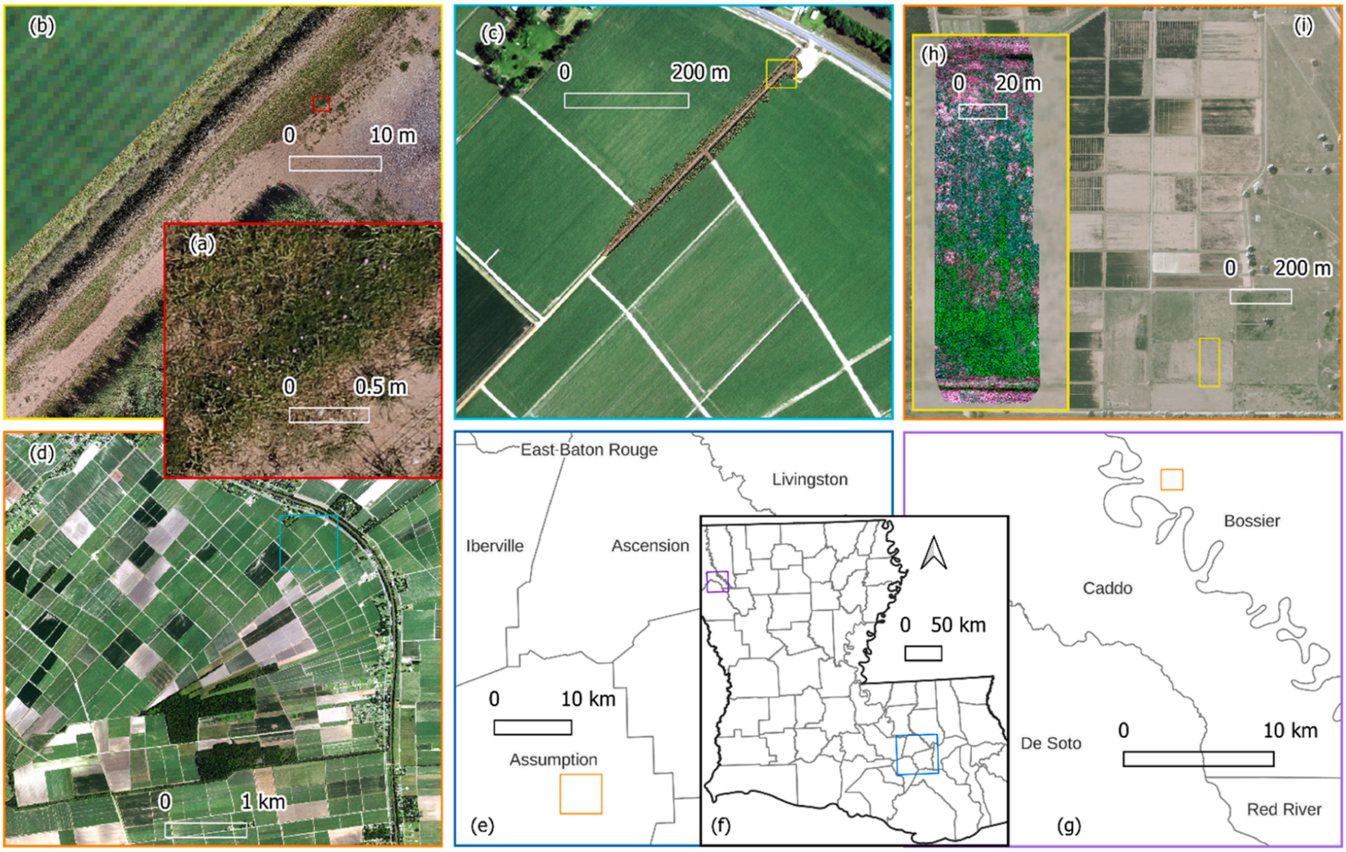

Fig. 3. Locations of image data collection for TensorFlow model for identification of Herbaceous mimosa. High resolution UAV (Unmanned Aerial Vehicle) derived map (0.389 cm) for the Napoleonville location is shown in panel a and b with the background of aerial image data from USDA National Agricultural Imagery Program (NAIP) with image date of 2019–07–07 (panel c and d). The Napoleonville location with the perspective of Assumption parish in Louisiana (f). Typical resolution (1.1 cm) of aerial map derived using UAV with MicaSense multispectral sensor for the Bossier parish (g) location is shown in panel h with the background of NAIP data (image date of 2019–08–13) in panel i.

Fig. 4. Example of image data used in this study showing images of herbaceous mimosa in the top row and other ground covers in the bottom row.

Fig. 5. Example of image data annotated as mimosa with the case of near the minimum 25 % threshold of mimosa in the image (a), containing mixture of other plant (not more than 15 %) (b), practically pure of mimosa plants in the image (c), and image data annotated as non-mimosa ground covers with the case of practically bare ground image (d), mixture of other plants (e), and homogenous image of other plants (f).

Table 1
List of key hyperparameter for TensorFlow deep learning algorithm used in this study.

Hyperparameter	Value Used	Description
Image Size	180	Fixed image size (pixels) used in the processing
Batch Size	10	The number of training and validation iterators
Filter Size	128	Number of filters that the convolutional layer will learn
Kernel Size	3 × 3	Matrix size used in convolution operation
Strides	2	Number of units the kernel shifts at each step

type of model application, which is relatively simpler data involving a single object. This could be the reason why validation accuracy fluctuated and the requirement of relatively large number of epochs needed to make the model relatively stable.

Although the TensorFlow approach is promising for use in the next step of moving toward field level mapping of herbaceous mimosa, an alternative approach of direct image classification based on spectral characteristics should also be tested to see if such an approach can perform relatively well while requiring much less computing time. TensorFlow processing in this study required relatively heavy computing resources. It took 20.12 h total to complete the 250 epochs of model runs involving 10 batches and 2116 input images with the average run of 4.828 mins per epoch with 16 GB RAM AMD Ryzen processor PC. The most efficient run with 842 total images and still achieving reasonable final accuracy of more than 0.95 had a total processing duration of 7.3 h with the average run of 1.749 mins per epoch. It is yet to be tested if the already built model from this study can be directly applied to read UAV-based ground cover images and able to perform with a similar high accuracy level.

5. Conclusion

This study found satisfactory results of applying a TensorFlow model for identification of herbaceous mimosa (*Mimosa strigillosa*) from other ground cover images with final validation accuracy of 95 % or higher. This achievement is rather ambitious given the nature of raster data used for image detection is far more complex than the typical examples of how TensorFlow models are usually applied to simpler data involving a single object, for example. The data preparation requirements as well as the heavy computing requirements of this TensorFlow approach provide a downside of this approach, especially if replication is required for each new species, for example.

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Ethical statement

The authors declare for the manuscript “Application of TensorFlow model for identification of herbaceous mimosa (Mimosa strigillosa) from digital images” the following is fulfilled:

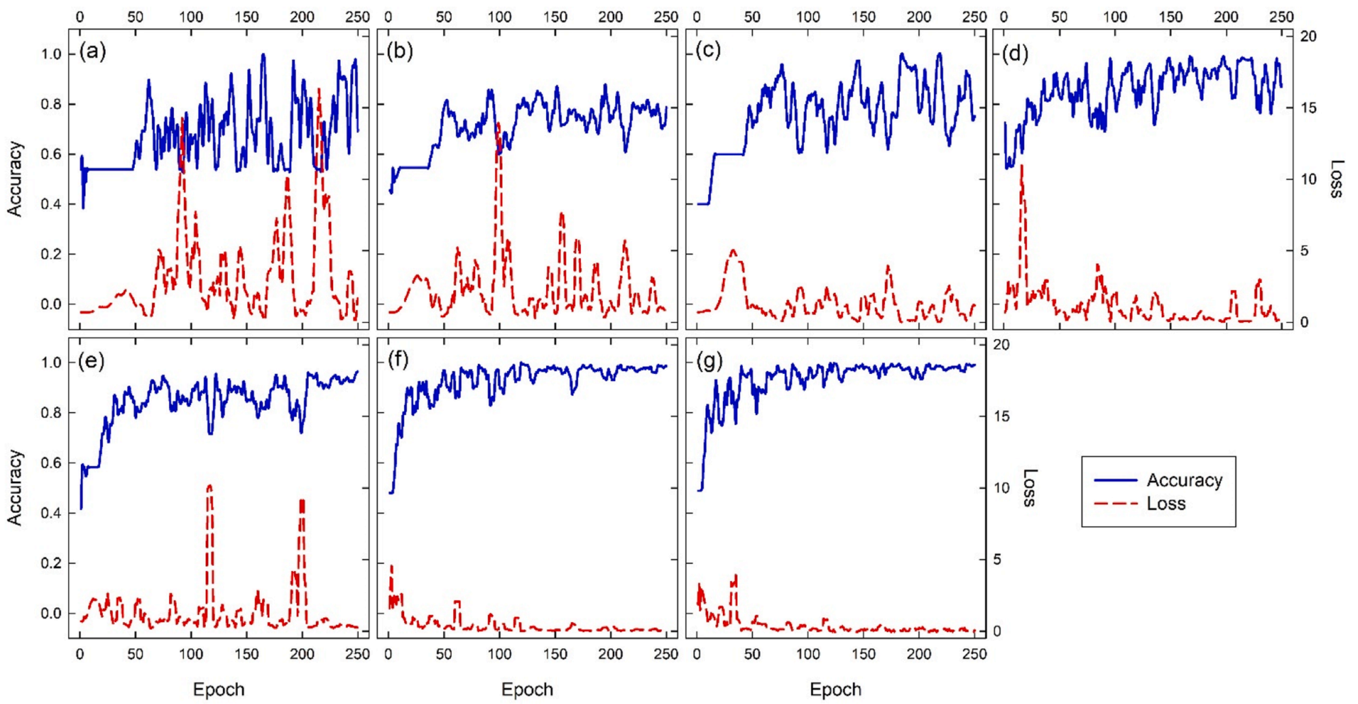

Fig. 6. Performance of TensorFlow model in identifying herbaceous mimosa *(Mimosa strigillosa)* from digital images showing the loss values and validation accuracy when run with the following total images: 134 (a), 154 (b), 168 (c), 422 (d), 842 (e), 1678 (f), and 2116 (d).

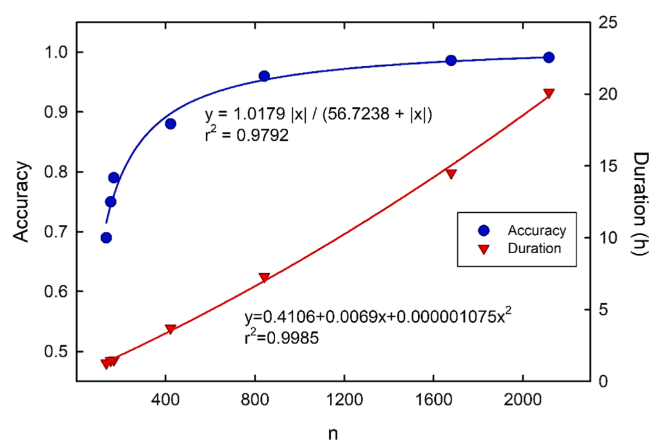

Fig. 7. Validation accuracy and processing duration of TensorFlow model in identifying herbaceous mimosa *(Mimosa strigillosa)* from digital images.

- This material is the authors' own original work, which has not been previously published elsewhere.
- The paper is not currently being considered for publication elsewhere
- The paper reflects the authors' own research and analysis in a truthful and complete manner
- The paper properly credits the meaningful contributions of co-authors and co-researchers
- The results are appropriately placed in the context of prior and existing research
- All sources used are properly disclosed (correct citation)

CRediT authorship contribution statement

T. Setiyono: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **T. Gentimis:** Conceptualization. **F. Rontani:** Investigation. **D. Duron:** Investigation. **G. Bortolon:** Investigation. **R. Adhikari:** Investigation. **B. Acharya:** Investigation. **K.J. Han:** Writing – review & editing, Conceptualization. **W.D. Pitman:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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