Intelligent Drought Stress Monitoring on Spatio-Spectral-Temporal Drone based Crop Imagery using Deep Networks

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Abstract

In recent years, high-put crop monitoring methods that integrate drone-based imagery and deep learning have been used to identify crop health and diseases. However, existing methods follow manual methods to study drought stress making it more challenging. To alleviate this problem, we propose a deep learning-based framework to identify drought-induced stress in maize using RGB and multispectral data. For this study, we conducted an experiment to grow maize crop in controlled conditions of water. A pipeline for pre-processing UAV-based images and extracting the region of interest from orthomosaic is explained. We used a variant of convolutional neural network-long short-term memory (CNN-LSTM) network to learn spatio-spectral-temporal patterns on drone-captured maize for water stress classification. We employed fine-tuned versions of pre-trained Alexnet, VGG 19, Resnet-18, Resnet-50 and Mobilenet V2 models for feature extraction and the LSTM model for sequence prediction on RGB data and multispectral data. It can be noted that multispectral data performed better than RGB data on drone captured data.

Introduction

Water stress or drought is a significant threat globally to crop production, primarily due to rapid climate changes. It is characterised by limited water resources that affect agricultural productivity. In the context of global warming, it is expected to cause warmer and drier conditions leading to severe droughts. In addition, drought stress will impact the economy due to the conflict between food demand and the growing population. Therefore, it is crucial to identify the drought-stressed crops and optimise the agronomic inputs to reduce the physiological damage and yield loss of crops.

High-throughput crop phenotyping with remote sensing technologies, namely, satellite-based and Unmanned Aerial Vehicles (UAV) based, have unravelled new possibilities for non-destructive prediction of crop yields. UAVs/drones became a new frontier among remote sensing platforms for their low cost and efficiency. These are used to obtain high-resolution aerial images that can provide a quick and non-intrusive view of crop growth status and water stress and, thus, yield prediction. Various optical sensors such as RGB, thermal, multispectral and hyperspectral cameras can be mounted on drones to collect crop canopy information (Xie and Yang 2020).

Existing crop stress classification techniques have relied on visual features by humans, which is inefficient. This problem can be addressed by computer vision and machine learning, which will allow for scalable, accurate high-throughput phenotyping (Ghosal et al. 2018). Deep learning (DL) has become one of the most efficient methods for object recognition and classification among machine learning methods (LeCun, Bengio, and Hinton 2015). DL methods surpassed conventional machine learning techniques as the former do not require handcrafted features, unlike the latter. DL methods have unlocked the prospects for interpreting enormous amounts of data and have percolated into data analytics in agriculture. Lately, multispectral data has been of paramount importance due to its additional bands, such as near-infrared and red-edge, with underlying information on crop stress. Deep learning based methods are well known to be integrated with multispectral image data. Multispectral data is known to perform better in classification tasks compared to RGB data (Wang et al. 2022) (Navarro et al. 2021).

Maize is one of the most adaptable crops that can thrive in various climatic settings. It is a staple food around the globe and accounts for 36% of the world's grain production and constitutes nearly 9% of the Indian food basket (IIMR 2020). The deficiency of water causes several physiological changes in maize crop, such as yellowness in the leaves and reduction in leaf area and biomass. Since there are one to two ears per plant, drought stress affects the quality, harvesting ability and crop yield (Zhou et al. 2020)(Liu et al. 2020).

Owing to the potential that maize occupies a significant amount towards ensuring the food supply, especially in developing nations like India, there is an immediate need to develop crop monitoring methods for accurate and early identification of drought-related stress. The present work uses time-series DL techniques to identify water stress crops captured using the drone.

Related works

Multispectral data give decent information about plant stress indicated by chlorophyll content changes (Zarco-Tejada, González-Dugo, and Berni 2012). RGB data is crucial for classifying drought affected crops due to its rich properties of colour and texture. However, its quality is particularly

Treatment	Detail
N_1	High Nitrogen stress
N_2	Optimum nitrogen
N_3	Overdose nitrogen
I_1	High water stress
I_2	Moderate water stress
I_3	No water stress

Table 1: Treatment information of the field

Bands	Wavelength [nm]
Blue	475
Green	560
Red	668
Red Edge	717
Near Infrared	842

Table 2: Wavelength Information of bands of Micasense Rededge Camera [nm]

light-sensitive and can only provide details from the visible spectrum. The ability to capture information from the invisible spectrum using multispectral data greatly aids in the detection of drought stress in the crops (Wang et al. 2022).

According to previous studies, drones equipped with optical sensors like RGB and multispectral can detect water and other sorts of crop stress (Calderón et al. 2013; Zhou et al. 2021). Multispectral sensing and machine learning together hold potential for the shift to data-driven agriculture. Various studies used spectral monitoring and machine learning to detect drought stress in crops (Virnodkar et al. 2020; Singh et al. 2016; Barradas et al. 2021; Spišić et al. 2022).

Data Acquisition & Pre-Processing

Experimental Site

The experimental study was conducted during the Rabi (post-monsoon) season in 2018-19 in a semi-arid zone of Hyderabad, Telangana, India. Maize crop (Zea mays L.) of variety 'Cargil 900 m gold' was selected for the research. The farm was maintained by Agro Climate Research Center, Professor Jayashankar Telangana State Agriculture University (PJTSAU), Hyderabad, India shown in the Appendix Figure 6(B). The experiment field was designed in a split mode with three nitrogen supply levels, and three irrigation levels based on a climatic approach (Halagalimath et al. 2017).

The experimental field consists of 30 subplots, each plot of size 4.2 $m \times$ 4.8 m. The field is supplied with water and nitrogen according to irrigation and cumulative pan evaporation ratio. Three nitrogen fertilisation levels and three irrigation levels resulted in nine distinct plots. For every water stress treatment, three replicates were grown, resulting in 27 subplots, as shown the Appendix Figure 6 (B) and 6 (C), while the remaining three subplots are dummy. Each plot was supplied with one of the nine treatments of water and nitrogen subjected to various stress conditions as shared in Table 1.

Data Acquisition

For geo-referenced data acquisition, Nine ground control points (GCPs) surveyed with Trimble R10 GNSS Receiver were deployed on the field. The images were acquired by flying DJI Inspire-1 Pro equipped with Micasense Rededge multispectral camera. The drone was flown at the predetermined flight plan using Mission Planner software at $10m$ altitude with a speed of 4 km/hr, and 80% overlap is maintained between two consecutive images in the X and Y direction. It collects data in five spectral bands, namely, blue, green, red, red-edge and NIR regions with dimensions of 1296 × 960 pixels keeping a pixel size of 1 cm displayed in Table 2. Sensor calibration was carried out using the reflectance panel depicted in Appendix Figure 1, and panel images were taken during the data-collecting procedure.

Preprocessing of UAV images

Calibration is necessary to account for the illumination at the time of image capture as accurate reflectance values indicate crop health status and for comparing imagery from day to day or season to season. The panel images captured during flight were loaded along with a calibration target values provided by the manufacturer of Micasense Rededge was recorded to perform radiometric calibration on Metashape Agisoft Photoscan photogrammetry software. To obtain a complete field perspective, the raw photos were also aligned, geo-rectified and stitched based on similar characteristics in the images. Following alignment, the high-quality and mild filter mode options were used to create the Dense Point Cloud. A digital elevation model (DEM) and an orthomosaic — a panoramic picture stitched together and geometrically corrected — of the region covered by all of the raw images were exported. It uses bilinear interpolation in the creation process of orthomosaic. Orthomosaic is further split into plot-wise images by running the QGIS tool using shape files and R software as shown in the Appendix Figure 4.

Methodology

In this work, drought-stress analysis in maize crop is studied. Maize crop when subjected to water-stressed treatment results in the reduction of leaf water evaporation process thus, surface area of the leaf decreases thereby twisting and rolling of the leaf occurs and the cholorophyll content is reduced. We further analyse how CNN and LSTM based deep networks used for water-stress identification using time-series RGB and multispectral data.

Multispectral Image Feature Analysis

For decades, vegetation indices calculated by integrating data from the visible red and near-infrared bands have been used to identify these crop health concerns. It gives information about revealing plant stress indicated by chlorophyll content changes. Adding red-edge band information to the existing vegetation indices allowed users to identify abnormal crop health in the early crop growth stages.

With the advent of the multispectral sensor, we can capture RGB, NIR and Rededge data simultaneously. RGB images provide rich colour information, whereas NIR, located in the electromagnetic spectrum between the visible and mid-infrared bands, provides more edge information even in low light conditions. The Rededge band, which lies between the Visible Red and Near Infrared bands, ranges approximately from 670 to 760 nanometers. It is the region where green vegetation's spectral reflectance fluctuates quickly, thus an excellent indicator of vegetative health (Xie et al. 2018). Appendix Figure 5 shows multispectral image samples captured by the drone. It is observed that all the bands reflect different characteristics of the same target.

Data Preparation

We consider three class water-stress classification, namely highly water-stressed, moderately water-stressed and unaffected, keeping optimum nitrogen from the treatments I1N2, I2N2 and I3N2, respectively. The crop images containing the region of interest are extracted from the net area of the plot. Multispectral data image channels are loaded using a custom data loader function. Each plot is further split into patches of 145 x 145. The images are loaded into a sequence of the length of the days on which the data is captured. Hence, each input data sequence contains thirteen images corresponding to the data collection date. The data is divided into 80% training data, and 20% testing data using the scikit learn train test split function.

Mathematically, an image of an input sequence i_t defined at timestep t, $t \in R^{m \times m}$, where m = 145 due to image dimension. An image sequence can be defined as given in the equation 1.

$$I = \left\{ i_t \mid t, t \in N, 1 \leq t \leq 13, i_t \in R^{m \times m} \right\} \tag{1}$$

Model Training

CNN Feature Extractor: CNN-based deep neural networks such as Alexnet, VGG-19, Resnet-18, Resnet-50 and Mobilenet V2 models are used for the feature extraction process. In case of RGB data, pre-trained models are fine-tuned on our maize data and the models are trained from scratch in case of multispectral data.

LSTM Predictor: The number of sequentially connected units is equal to the days the data is captured. In our work, the data was collected from the 25th Day of Sowing to the flowering stage of maize. We consider thirteen days of sequential data in our work. The output of the LSTM network is given to two dense layers followed by a softmax output layer of size three since there are three categories to be predicted. CNN- based models were used to extract features from images of a sequence such that its weights remain the same for all the timesteps in the LSTM network. Output sequence can be defined as given in the equation 2.

$$X = \left\{ x_t \mid t, t \in N, 1 \leq t \leq 13, x_t \in R^d \right\} \tag{2}$$

where x_t denotes Feature at timestep t.

This output feature is fed to LSTM network. This hidden vector h_t of LSTM is fed to the dense layer and softmax function for further classification. The softmax function is responsible for obtaining class-wise probability.

Model	Train Accu.	Val. Acc.
Alexnet-LSTM	86.444	85.455
VGG-19-LSTM	87.764	86.182
Resnet-18-LSTM	89.202	85.455
Resnet-50-LSTM	92.506	86.727
MobileNetV2-LSTM	94.944	86.455

Table 3: Accuracy results on RGB data.

Model	Train Loss	Val Loss
Alexnet-LSTM	0.599	0.593
VGG-19-LSTM	0.656	0.620
Resnet-18-LSTM	0.208	0.147
Resnet-50-LSTM	0.596	0.572
MobileNetV2-LSTM	0.603	0.593

Table 4: Loss Information on RGB data.

$$Softmax\,(p_i) = \frac{\exp^{p_i}}{\sum_{j=1}^{C} \exp^{p_j}} \tag{3}$$

Comparison of Methods

The performance of CNN-LSTM based deep networks in case of RGB data and multispectral data is compared. The training was performed for 50 epochs with batch size of 12. Adam optimizer was used as a cross-entropy loss function. For the performance analysis of the proposed model, the performance metrics such as Precision, Recall and F1-score were used.

$$Recall = \frac{TP}{(TP + FN)} \tag{4}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{5}$$

$$F1 - score = \frac{(2 \times Recall \times Precision)}{(Recall + Precision)} \tag{6}$$

Results & Discussion

The performance results of models used for both RGB data and multispectral data are listed in the Tables 3, 4, 5, 6, 7, 8 respectively. It is observed that Mobilenet V2, Resnet 50 performed well with high training and validation accuracy in case of multi spectral data compared to that of results on RGB data. This may be due to the addition of spectral component in addition to their rich model complexity and feedback mechanisms that can capture the visual changes in drought-stressed plants. The validation loss values can be further reduced by increasing the dataset size and using various data augmentation techniques to make the model robust enough to test on field scenarios.

The accuracies may be affected due to bilinear interpolation used in AgiSoft software for drone data processing. Considering raw images and extracting the region of interest from the plots can be done for effective classification results.

Model	Precision	Recall	F1-Score
Alexnet-LSTM	0.9523	0.9487	0.9505
VGG-19-LSTM	0.9333	0.9230	0.9281
Resnet-18-LSTM	0.9523	0.9487	0.9505
Resnet-50-LSTM	0.9743	0.9743	0.9743
MobileNetV2-LSTM	0.9523	0.9487	0.9505

Table 5: Classification Results on RGB data

Model	Train Accu.	Val. Acc.
Alexnet-LSTM	82.1	85.348
VGG-19-LSTM	85.3	84.483
Resnet-18-LSTM	88.4	86.552
Resnet-50-LSTM	97.6	87.034
MobileNetV2-LSTM	95.4	92.924

Table 6: Accuracy results on Multispectral data.

Model	Train Loss	Val Loss
Alexnet-LSTM	0.483	0.5714
VGG-19-LSTM	0.513	0.657
Resnet-18-LSTM	0.428	0.364
Resnet-50-LSTM	0.511	0.521
MobileNetV2-LSTM	0.521	0.572

Table 7: Loss Information on Multispectral data.

Model	Precision	Recall	F1-Score
Alexnet-LSTM	0.8821	0.7858	0.8311
VGG-19-LSTM	0.9265	0.8954	0.9106
Resnet-18-LSTM	0.9765	0.9457	0.9608
Resnet-50-LSTM	0.9642	0.8975	0.9296
MobileNetV2-LSTM	0.9143	0.9456	0. 9296

Table 8: Classification Results on Multispectral data

Next Steps and Future Work

We found from our data that RGB images contain rich features of color, texture and profile that are essential for classifying drought affected crops. However, the quality of RGB images is very sensitive to light and can only present information in the visible spectrum. Near-Infrared band highlights the edges and these egde data can distinguish unaffected and stresssed crops as stressed crops have leaf-rolling and leaf area decreases. Red-edge band is known to show vegetative stress at first. Thus, these bands allow to capture the information underlying in invisible spectrum thereby significantly helps with the detection of early crop deficits.

Therefore, considering that the spatial and spectral image features may have different influences on the measurement results, we propose to develop a novel method of weighted feature fusion. Before feeding the output features of the two feature layers into the classification layer, the weighted feature fusion is carried out first. The weights are multiplied by the output feature vectors of the two CNNs, and then the two feature vectors are concatenated. The formula of feature fusion is shown in Equation 7.

$$feat = \lambda_1 * feat_a \oplus \lambda_2 * feat_b \tag{7}$$

where λ_1 and λ_2 are learnable weight values of spatial and spectral networks respectively; $\oplus$ represents concatenate operation; $feat_a$ and $feat_b$ are feature vectors extracted by spatial and spectral networks respectively; $feat$ is global features after feature fusion.

As an improvement of artificially assigning feature weights, we propose a self-learning method for feature weights, in which the fusion weights also are calculated by learning with training. In the initial stage, two weights λ_1 and λ_2 can be set to 0.5 by adopting the strategy of balancing weights. Also, on each day of capture, classification test is performed to identify the crops that are drought affected at early stages.

$$Loss_w = [1 - (\lambda_1 + \lambda_2)]^2 \tag{8}$$

Conclusion

In this paper, we addressed how to identify drought-stressed crops by using sequential based deep learning methods. This work is an effort to automate the problem of water stress identification task. RGB and multispectral data acquired by the drone are used and compared by employing CNN-LSTM-based models. It is observed that multispectral data include add NIR and Rededge bands in addition to visible spectrum that provide better results than RGB data. Further, we are developing a novel model that captures spectral, spatial and temporal information to identify the drought stress at early crop growth stages. Thus, this work would aid agricultural scientists in their analysis for developing new crop varieties that can sustain the climatic changes and require less agronomic inputs.

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Appendix

A: Supplementary Figures

Figure 1: Calibrated reflectance panel which was used for data multispectral data acquisition.

Figure 2: Drone flying in the field

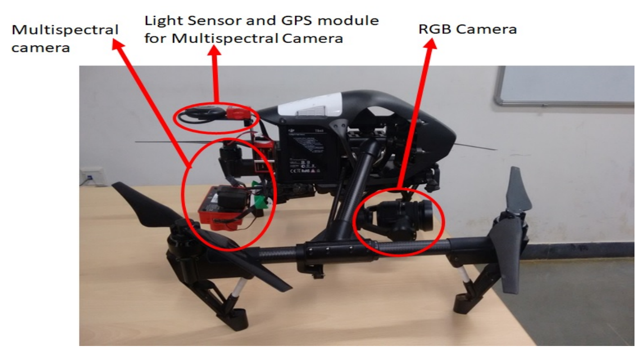

Figure 3: Drone equipped with multispectral camera

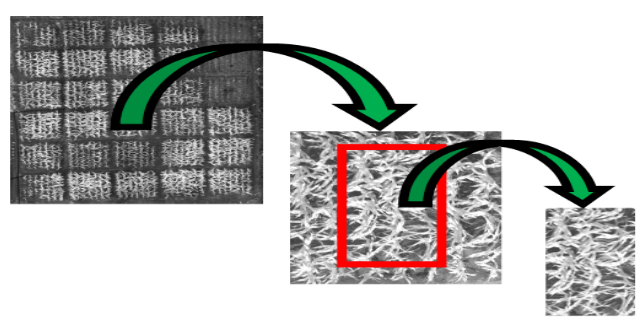

Figure 4: Orthomosaic and plot segmentation of maize crop

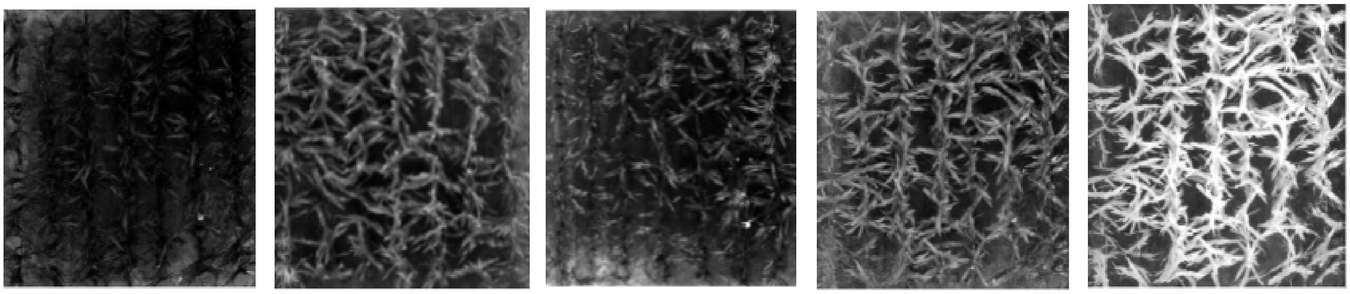

Figure 5: Band Images of Multispectral data of Maize. (a) Blue (b) Green (c) Red (d) Near-Infrared (e) Rededge.

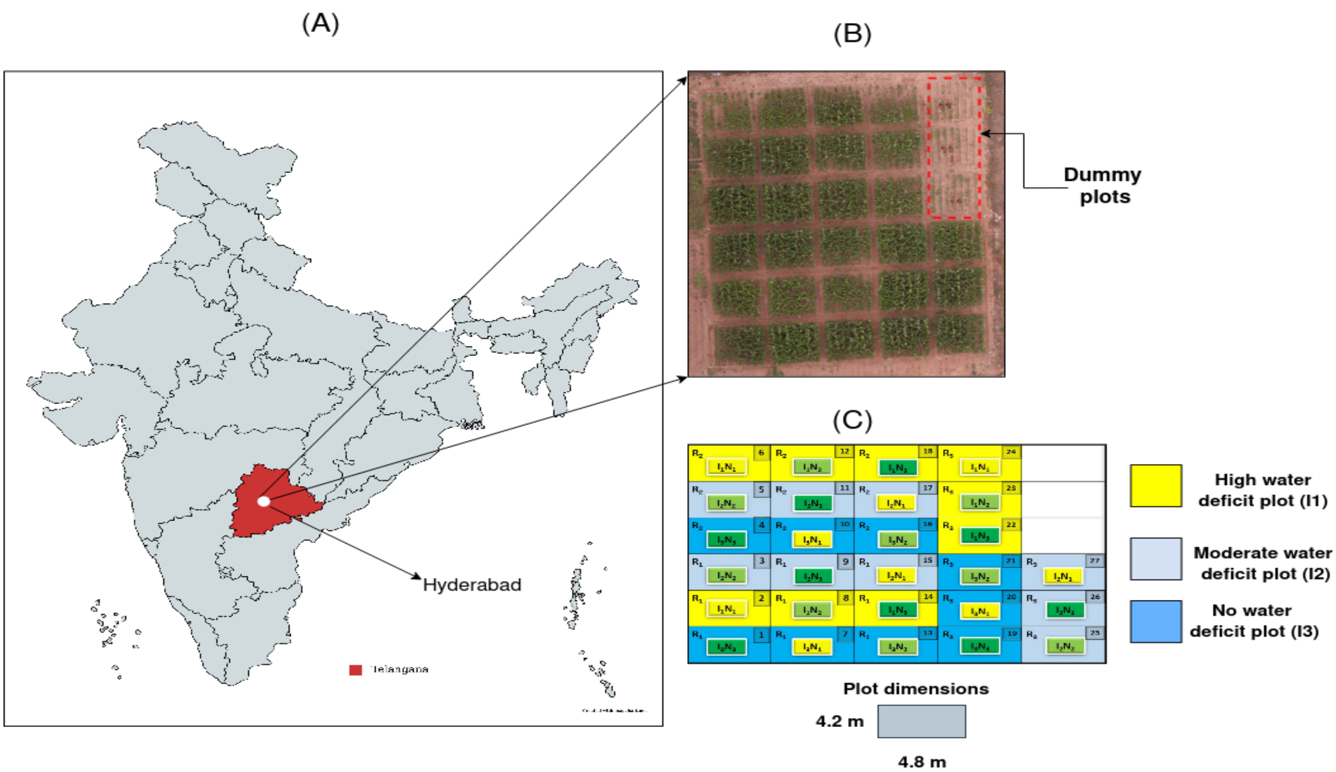

Figure 6: (A) Experiment field highlighted in the Indian map (B) Top-view of the field captured by the drone (C) Field layout of treatments of each plot of size $4.2m \times 4.8m$ where I_1, I_2, I_3 represent low, moderate and high treatments of water respectively.

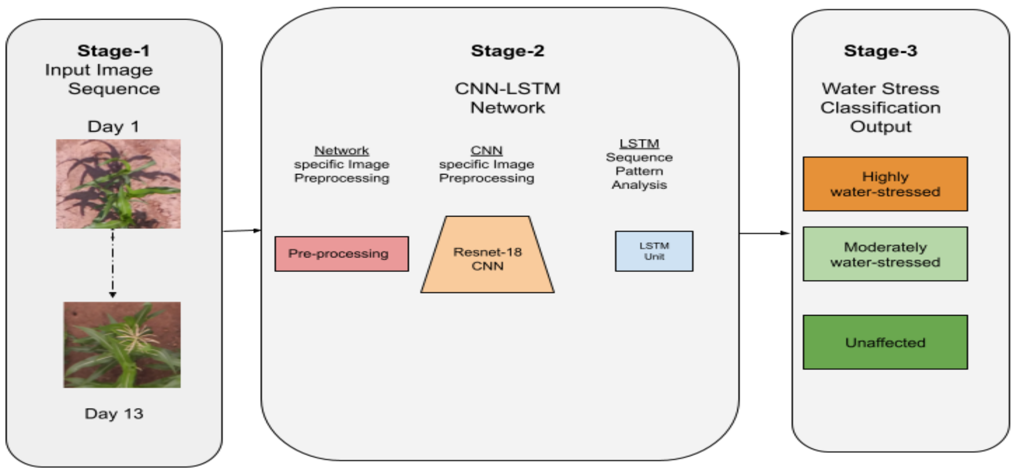

Figure 7: Pipeline of DL drought stress classification model for drone based maize crop patches. RGB image shown for visual representation.