Multispectral Image Classification with Computational Intelligence Techniques using UAV Multispectral Data for Ecology and Sustainability Applications

DOCTORAL DISSERTATION PROPOSAL

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Presentation Time - 10.00 am

Presentation Outline

Introduction and Background

- Problem Overview
- Literature Review: The “State of the Art”
- Limitations of existing techniques

Problem Statement

- Problem Statement Explained
- Dissertation Objectives
- Work plan

Contribution

- Publications

Preliminary Results

Data set Overview

DNN Architecture

Conclusion

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Introduction and Problem Background

- Forests account for 30 percent of the land.
- Forest fragmentation may result due to natural and man-made factors.
- Restoring forest ecosystems has become an increasingly high priority.
- Meeting the restoration goals requires quantifying metrics of vertical and horizontal forest structure.

Figure 1. Fragmented oak and pine forest

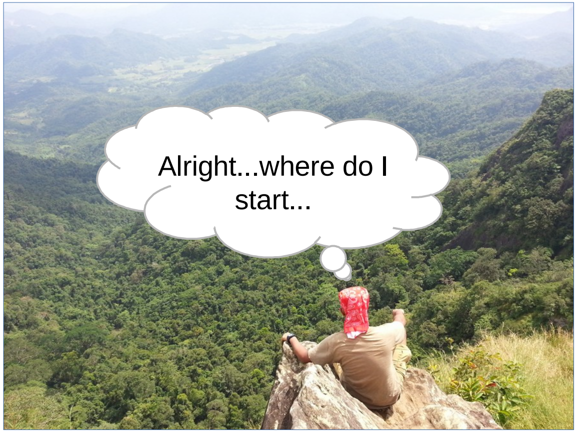

Figure 2. Topographic view of a tropical forest

Introduction and Background Contd.

- Remote Sensing platforms
  - Satellites
  - Manned Aircraft
  - Unmanned Aerial Vehicles

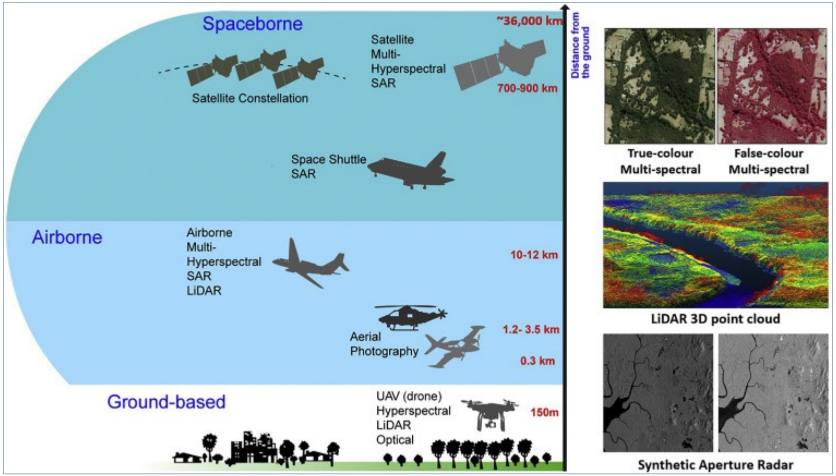

Figure 3. Common remote sensing platforms, sensor combinations and Remote-Sensing data

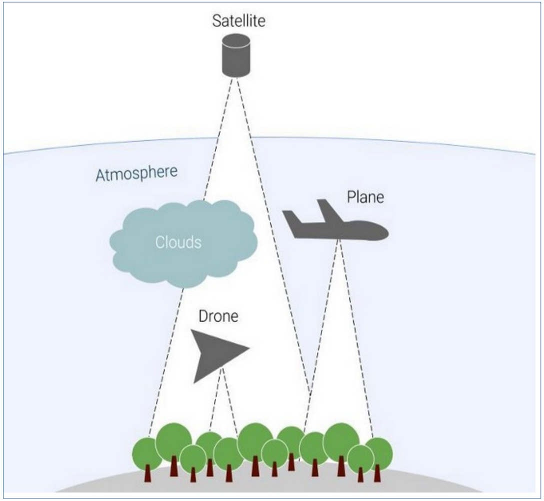

Figure 4. Spatial resolution of different techniques

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Introduction and Background Contd.

- Advantages of UAV based remote sensing
  - Improved range and precision
  - Easy access to remote terrain
  - Centimeter level resolution for application requiring accurate maps
  - Greater accuracy

Figure 5. Custom-built quad copter at UDM Robotics lab

Figure 6. Hexacopter deployed for agriculture applications

Objective

- Understand current systems used in CI to model ecological dynamics.
- Further these studies of integration with a custom UAV.
- Final goal – Automate ecological dynamic decision of forests using CI as the model and sensors as input.
- Applications – Forestry, Agroindustry, Green technology startups, etc.

Literature Review : The “State-Of-The-Art”

- Tree Density Mapping
- Stand Count
- Tracking Tree health
- Disease Monitoring and Identification
- Invasive Species detection
- Species Classification

Tree Density Mapping

- Traditional method – Point centered quarter sampling
- Remote sensing techniques
  - Indices calculation
  - Regression analysis

Camera	Algorithm	Accuracy
Rikola hyperspectral [42]	2D confidence map	97.3 %
RGB [43]	CNN	96.7 %
Parrot Sequoia multispectral [44]	Faster RCNN	95 %
RGB [45]	U-net	-
RGB [46]	Semi-supervised DNN	69%
DJI Phantom 4 RGB [47]	Supervised CNN	90%
Panasonic G3 RGB [48]	VisualSFM Tool	-
DJI Mavic Pro RGB [49]	Pix4Dmapper Pro Tool	89%

Table 1. Existing literature on Tree Density mapping

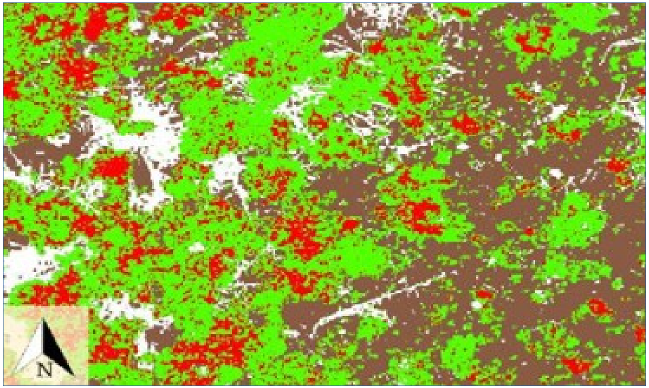

Figure 7. Tree density mapping using MicaSense RedEdge data (Juniper forest, Oregon) [41]

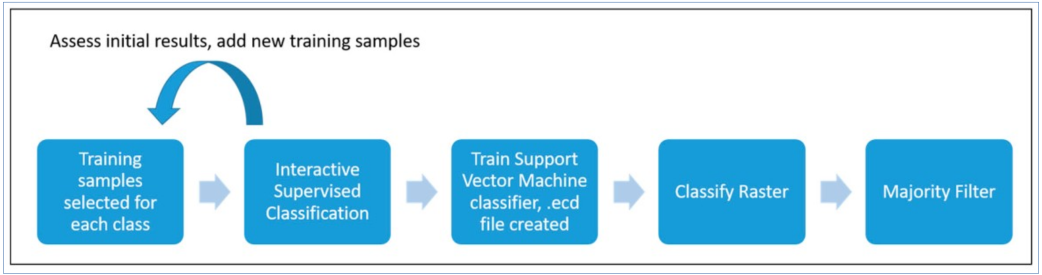

Figure 8. Example for Supervised classification performed in ArcMap

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Stand Count

- Traditional methods
  - Fixed area plot sampling
  - Variable area plot sampling
  - Foot surveys
- Remote sensing techniques
  - CIR composite imagery
  - Confidence map estimation

Camera	Algorithm	Accuracy
Nikon D800 RGB [58]	patch-based CNN	90 %
Parrot Sequoia multispectral [44]	Faster RCNN	95 %
DJI X5R RGB [59]	MaxArea Mask Scoring RCNN	82.7%
Multispectral [60]	LeNet CNN	95.11%
Digital RGB [61]	UNET	96.03%
Pushbroom Hyperspectral [62]	Hough transform	84.1%
Phantom 4 RGB [63]	CNN	91.3%
Garmin VIRB Ultra 30 RGB [64]	YoloV3	98%
UAS Multispectral [65]	Digital Elevated Veg Model	95%
DJI Phantom4 RGB [66]	Color-based segmentation	99.09%
DJI Mavic 2 Pro [67]	YoloV3	96%
DJI Phantom4 RGB [68]	Faster-RCNN	97%
RGB Orthomosaic [69]	FCRN	95-97%
DJI Phantom 3 [70]	Accelerated scale-space filter	94%
RGB [71]	R-CNN	91.8%

Table 2. Existing literature on Stand Count

Figure 9. CIR Composite band to estimate stand count [55], Captured with MicaSense Altum

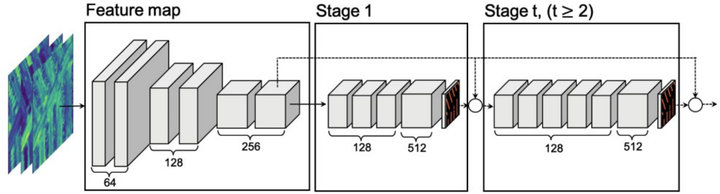

Figure 10. A simple model to estimate stand count using SGD Optimizer

Tracking tree health, Disease monitoring and identification

- Traditional methods
  - Foot surveys
- Remote sensing techniques
  - Indices calculation – NDVI map
  - CIR composite imagery

Camera	Algorithm	Accuracy
FPI hyperspectral [75]	SVM classifier	81%
Sony DSC-RX1RM2 [76]	DCNN + Adaboost classifier	95.7%
MicaSense RedEdge [77]	Random forest	69.4%
DJI Matrice multispectral [78]	YOLOv3	99.8%
DJI S1000 hyperspectral [79]	DCNN Inception-Resnet	85%
RGB [80]	Faster R-CNN	-
RedEdge-MX multispectral [81]	SCANet	79%
Headwall Nano-Hyperspec [82]	XGBoost classifier	97%
RGB [83]	Random Forest Fster R-CNN	82%
Parrot Sequoia multispectral [84]	SLIC Algorithm	96.24%
Resanon Pika L 2.4 camera [85]	RBF + KNN	92%
Sony A5100 RGB [86]	AlexNet, GoogLeNet	93.30%,97.38%

Table 3. Existing literature on disease monitoring and tree health

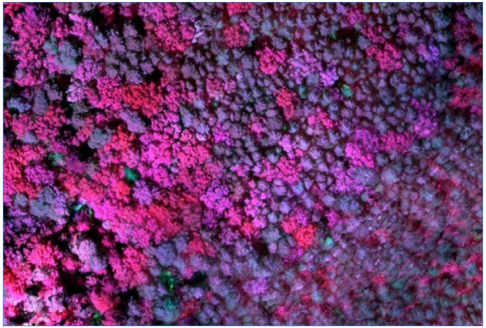

Figure 11. CIR Composite plot to determine tree health [74]

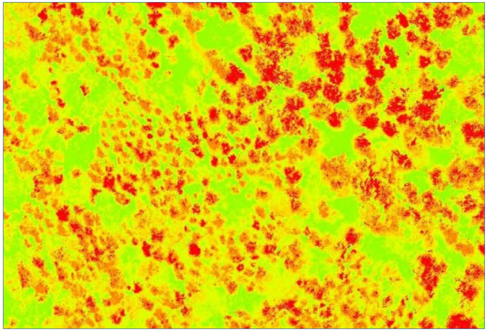

Figure 12. NDVI map to determine tree health [74]

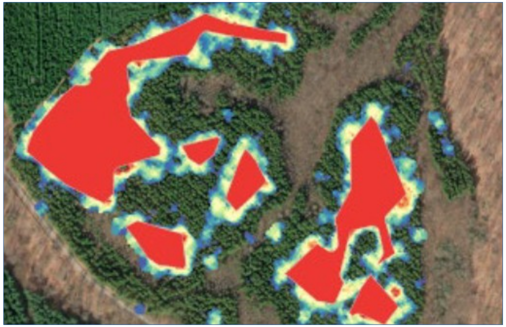

Figure 13. Infestation levels using RedEdge Band (left) [74]

Invasive Species Detection

- Invasive species disturb the balance in an ecosystem.
- Multispectral data from UAV can be used to find extent of invasion.
- Techniques :
    - Indices
    - Digital surface model

Camera	Algorithm	Accuracy
OXI-II hyperspec [89]	MaxEnt Classifier	-
DJI Phantom 3 RGB [90]	ISO cluster	90%
Canon S100 multispec [91]	Agisoft software	-
DJI Phantom 4 RGB [92]	Image processing	95%
Nikon D850 [93]	IAPsNet	93.39%
Ricoh GR3 [94]	Random forest	90%
FC350 RGB [95]	Cognition software	72%

Table 4. Existing literature on Invasive species detection

Figure 14. Mapping invasive species using GLCM +SVM

Note : The map shown in Figure 14 highlights the extension of a phragmites invasion in the coastal wetlands of the Gulf of Mexico.

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Species Classification

- Different plant species exhibit different reflectance properties.
- Species classification using advanced classification algorithms.

Camera	Algorithm	Accuracy
DJI Phantom 4 RGB [99]	Residual Network(ResNet)	97%
RGB [100]	Residual Network(ResNet)	80%
Samsung NX1000 RGB [101]	MLP + 3D-CNN	99.6% B
DJI Phantom 4 RGB [102]	GoogLeNet	89%
Sony DSC-WX220 RGB [103]	Random Forest with R	72%
DJI FC220 [104]	Adam Optimizer	98.143%
UX4 hyperspec [105]	SVM Classifier	72.4 %
DJI Phantom RGB [106]	ResNet-200	83.6%
Alpha 7R RGB [107]	Adapted U-net	86%
MicaSense Altum [108]	Random Forest	80.20%

Table 5. Existing literature on species classification

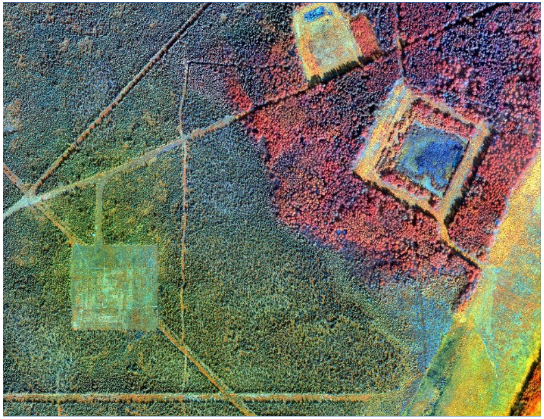

Figure 15. Map of different reflectance properties for species classification

Note : The orthomosaic map shown in Figure 15 highlights clearly the difference in reflectance properties of each tree species.

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Limitations of Existing Techniques

- None of the currently available techniques characterize the ecological (biotic/abiotic parts) environment.
- Biodiversity prediction and mapping of ecological system for the prediction of niches are missing in literature.
- No automated techniques available.
- No comparison with satellited based classification for accurate prediction.

Dissertation Objectives

- Detailed literature review about current system used in CI to model ecological dynamics.
- Automate important principles in ecology that helps to study evolution.
- Pre-processing of Altum data with image processing.
- Develop DNN for automating ecological dynamic decisions of forests.
- Evaluation of DNN.

Work plan

- Phase 1 - Detailed literature review + publication
- Phase 2 - Hardy-Weinberg automation + publication
- Phase 3 - RGB Image classification + publication
- Phase 4 - Development of custom UAV equipped with Altum multispectral camera
- Phase 5 - Data set collection
- Phase 6 - DNN development + publication
- Phase 7 - Automation
- Phase 8 - Final dissertation report + STEM journal publication

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Publications

MASAL 2020 Conference

- Title : A Survey of Computational Intelligence techniques in Ecology and Sustainability Engineering

- Authors : Karthika Balan, Dr. Michael Santora, Dr. Mariam Faied and Dr. Victor D Carmona-Galindo

- Abstract : In this paper a survey of current implementations with computational intelligence techniques in the area of ecology and sustainability is presented. The main aim of this review is to understand the current systems used in computational intelligence to model ecological dynamics and to further these studies of integration with a custom UAV equipped with state of the art sensors. The goal is to automate ecological dynamic decisions of forests using computational intelligence as the model and sensors as the input.

Publications

ACCTHPA 2020 IEEE Conference

- Title : Study of Evolution by automating Hardy-Weinberg Equilibrium with machine learning techniques in TensorFlow and Keras
- Authors : Karthika Balan, Dr. Michael Santora, Dr. Mariam Faied and Dr. Victor D Carmona-Galindo
- Abstract : This paper describes a new method that integrates Ecology and Engineering by automating the Hardy-Weinberg model using ADAM Optimization technique. The neural network trained based on Keras and TensorFlow has been deployed using python for the study of evolution. The developed model is tested with standard allele frequency database "ALFRED" to prove the efficiency.

Preliminary Results

- Hardy-Weinberg Automation
  - ADAM Optimization
  - Mamdani FIS
  - Monte-Carlo simulation
- RGB Tree crown detection
- Vegetation detection

Hardy-Weinberg Automation

- Integrate Ecology and Engineering by predicting evolution.
- Automate Hardy-Weinberg principle using ADAM Optimization in TensorFlow and Keras.

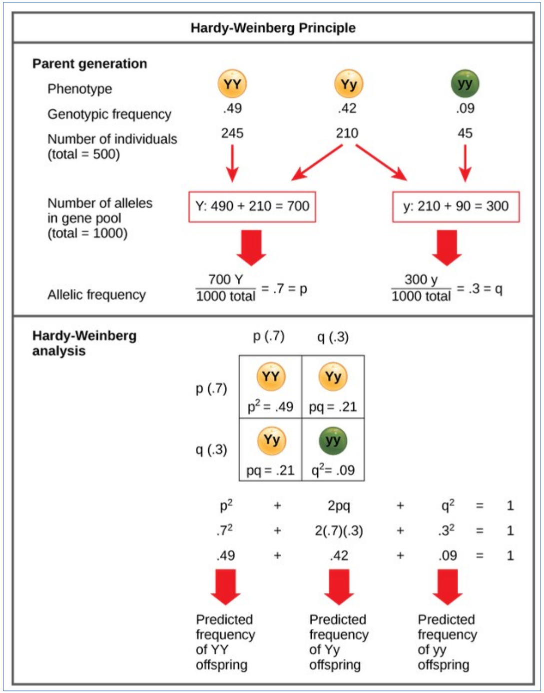

Figure 16. Concept of Hardy-Weinberg Equilibrium

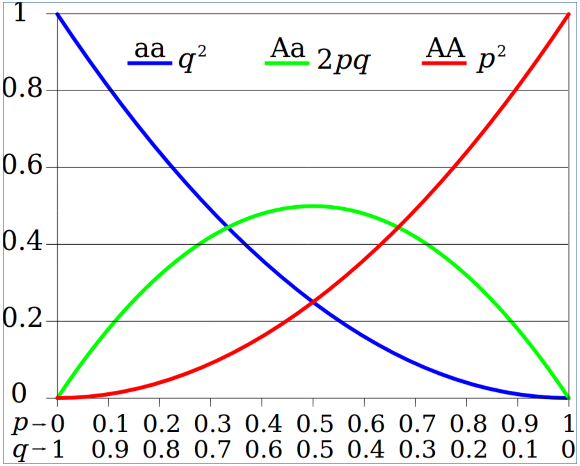

Figure 17. Graphical representation of allele frequencies in a population

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System modeling

- ADAM Optimization – Adaptive learning rate optimization technique.
- ADAM = Stochastic Gradient Descend with momentum + Root mean square propagation algorithm

PARAMETERS	GRADIENT DESCEND	RMS PROPAGATION
Moving Average	$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$	$v_t = \beta_2 v_{t-1} + (1-\beta_2) {g_t}^2$
N^{TH} moment	$m_n = (1-\beta_1) \sum_{x=0}^{n-1} \sum_{N} [g_n + \beta_1^x g_{n-x}]$	$v_n = (1-\beta_2) \sum_{x=0}^{n-1} \sum_{N} [{g_n}^2 + \beta_2^x g_{n-x}^2]$
Expected value of N^{TH} moment	$E[m_n] = (1-\beta_1) E[\sum_{x=0}^{n-1} \sum_{N} [g_n + \beta_1^x g_{n-x}]]$	$E[v_n] = (1-\beta_2) E[\sum_{x=0}^{n-1} \sum_{N} [{g_n}^2 + \beta_2^x g_{n-x}^2]]$

Table 6. Parameters for gradient descend + RMS Prop

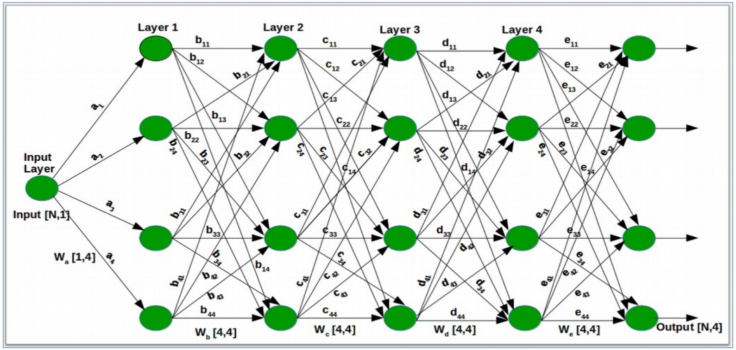

Figure 19. Neural network representation with four hidden layers

Algorithm: Generalized Adam

S0. Initialize $m_0 = 0$ and x_1

For $t = 1, \dots, T$, do

S1. $m_t = \beta_{1,t} m_{t-1} + (1-\beta_{1,t}) g_t$

S2. $\hat{v}_t = h_t(g_1, g_2, \dots, g_t)$

S3. $x_{t+1} = x_t - \frac{\alpha_t m_t}{\sqrt{\hat{v}_t}}$

End

Figure 18. Pseudo-code for ADAM Optimization

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Simulation Results

WEIGHTS LAYER 1 - NETWORK 1

b	1	2	3	4
1	1.621	0.0355	0.691	-1.245
2	-0.888	0.145	-0.567	0.442
3	-0.410	-0.329	0.201	0.293
4	0.300	-0.306	0.293	-0.859

WEIGHTS LAYER 2 - NETWORK 1

c	1	2	3	4
1	0.716	-0.399	-0.064	1.119
2	-0.416	0.616	-0.895	-0.590
3	-0.046	-0.193	-0.073	0.434
4	-0.616	1.037	-0.391	0.618

CALCULATED OUTPUTS FOR SET OF INPUTS

f(A)	f(a)	f(AA)	f(Aa)	f(aa)
0.82	0.1811	0.6945	0.2510	0.0524
0.24	0.7924	0.0213	0.3665	0.6103
0.57	0.4276	0.4212	0.2986	0.2796
0.95	0.0516	0.8367	0.2270	0.0618

CALCULATED OUTPUTS FOR SET OF INPUTS - NETWORK 2

f(A)	f(a)	f(AA)	f(Aa)	f(aa)
0.82	0.1800	0.6984	0.2512	0.0510
0.24	0.7614	0.0604	0.3615	0.5801
0.57	0.4292	0.4241	0.2970	0.2804
0.95	0.0496	0.8337	0.2259	0.0603

WEIGHTS INPUT LAYER - NETWORK 2

	1	2	3	4
a	-0.425	-0.045	0.384	-0.555

WEIGHTS LAYER 1 - NETWORK 2

b	1	2	3	4
1	0.434	-1.141	-0.243	0.149
2	-0.065	0.679	-0.190	-0.152
3	0.251	0.005	0.803	0.042
4	-0.810	-0.377	0.133	-0.867

WEIGHTS LAYER 2 - NETWORK 2

c	1	2	3	4
1	0.236	-0.350	-0.219	0.516
2	0.907	0.756	0.012	-0.151
3	0.597	-0.253	0.350	0.3377
4	-0.485	0.349	-0.840	0.069

WEIGHTS LAYER 3 - NETWORK 2

c	1	2	3	4
1	-0.918	0.302	-0.175	0.049
2	-0.118	0.403	0.234	0.407
3	0.484	-0.463	0.128	-0.323
4	-0.079	0.117	0.156	-0.043

WEIGHTS LAYER 4 - NETWORK 2

d	1	2	3	4
1	0.953	-0.829	0.215	0.203
2	-0.348	0.601	-0.187	-1.115
3	-0.272	0.223	0.017	0.005
4	0.031	0.338	0.553	0.303

Table 7. Calculated weights and outputs for set of inputs

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Simulation Results Contd.

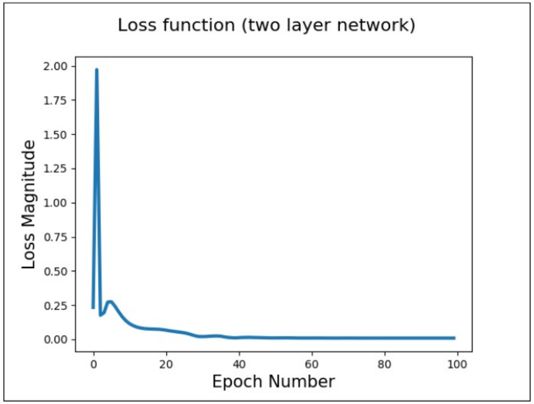

Figure 21. Mean square error loss for 2-layer network

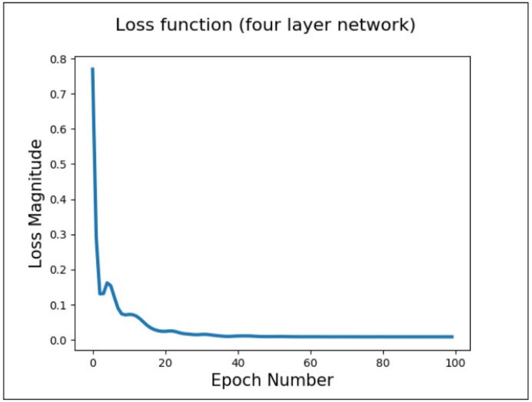

Figure 22. Mean square error loss for 4-layer network

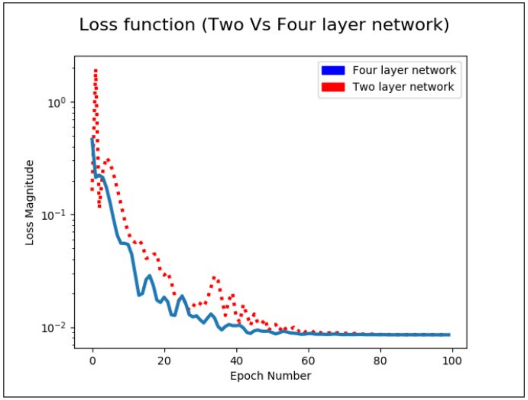

Figure 23. Mean square error loss comparison

Comparison Table

Automation method	Average Accuracy(in %)
ADAM Optimization (2 hidden layers)	88%
ADAM Optimization (4 hidden layers)	90.5%
Mamdani FIS	79.6%
Monte Carlo	94.2%

Table 8. Comparison table showing accuracy for different automation techniques

Applications

- Predict species evolution using multispectral imagery for forest reconstruction.
- Useful for common farmers to predict the crop cultivation for coming generations.
- This gives scientists a mathematical baseline of a non-evolving population to which they can compare evolving populations.

Tree crown detection from UAV RGB Images using DeepForest

- Can use 3D Lidar data + RGB data.
- DeepForest model provides easy access.
- Prebuilt model pretrained on tens of millions of LiDAR generated + hand labeled RGB crowns.
- While LIDAR data is used to facilitate data generation for the prebuilt model, prediction relies only on RGB data

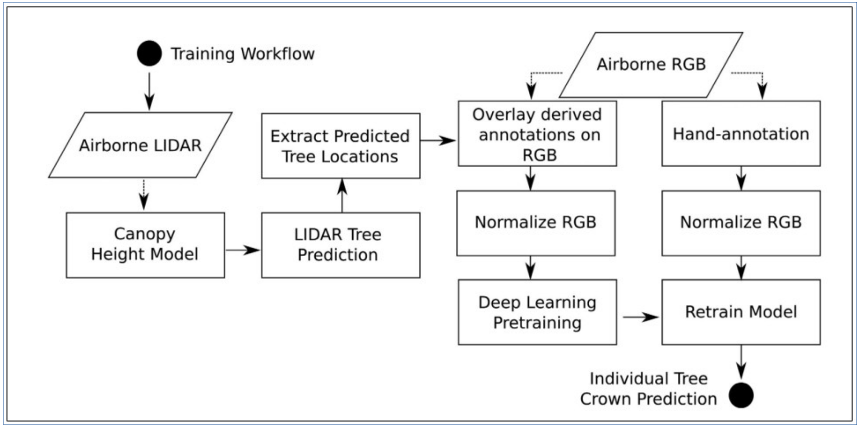

Figure 24. Prebuilt model training workflow

Simulation Results

Figure 25. Tree Crown detection sample output

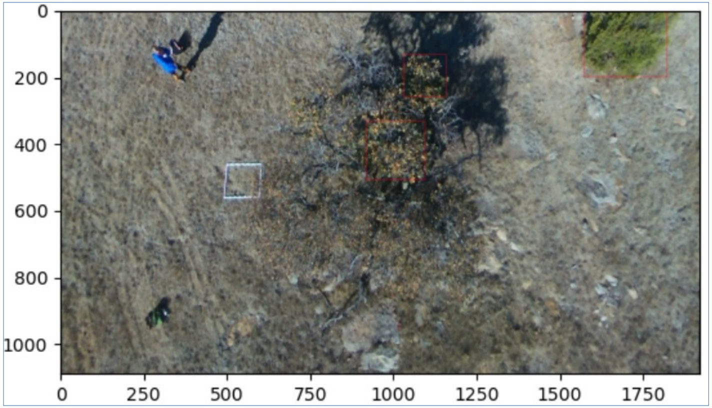

Figure 26. Tree Crown detection sample output

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Vegetation detection from Pumpkin Patch using ALTUM Multispectral Camera

- Variation in reflectivity of forest species helps in classification.
- Chlorophyll absorbs strongly in red and reflects most in NIR.
- NDVI = (NIR – R)/(NIR + R)
- Varies from -1 to +1.

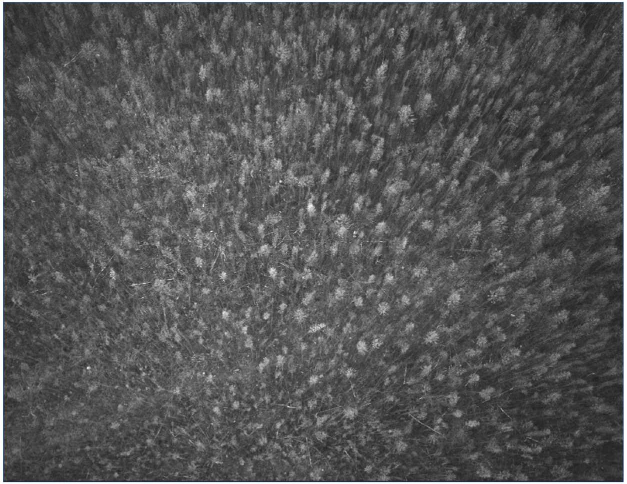

Figure 27. Sample image from pumpkin patch field

Figure 28. MicaSense Altum multispectral camera mounted on a DJI Phantom quadcopter

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Results

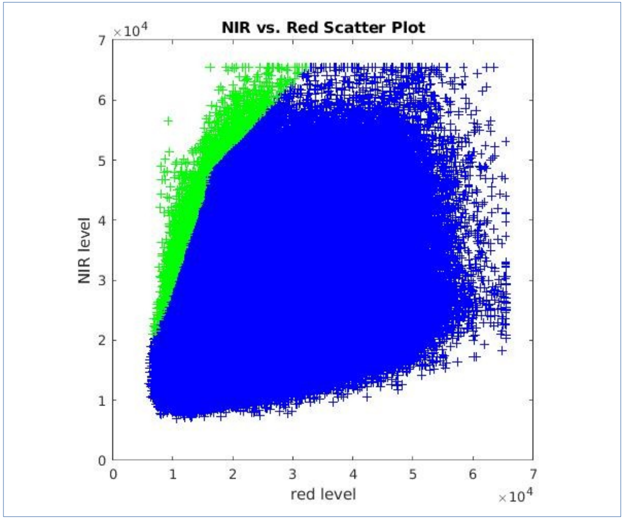

Figure 29. Scatter plot result from pumpkin patch data

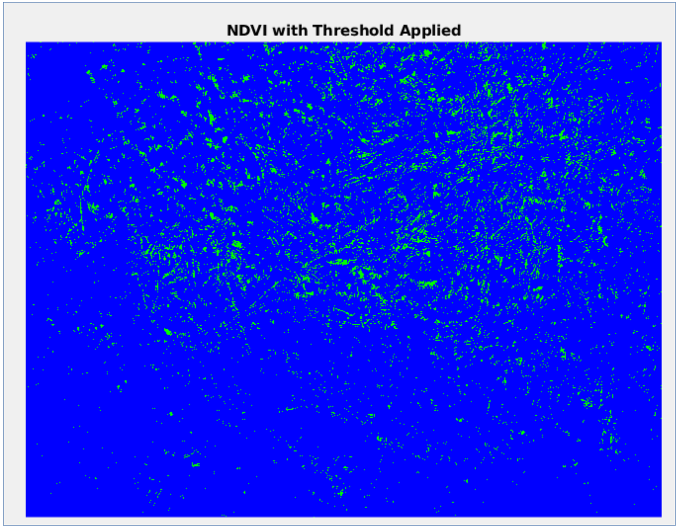

Figure 30. NDVI map with threshold applied

Percentage of vegetation = 12.4376%

Data Set Overview

- NASA Satellite Imagery Database
  - MODIS
  - LANDSAT
- DeepForest model database
- Parrot bebop RGB images Sierra Fria, Aguascalientes, Mexico
- Micasense Altum multispectral data real time image acquisition

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Data Set Overview

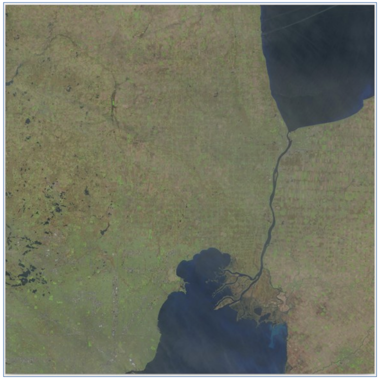

Figure 31. Sample LANDSAT data of areas near palmer park

Figure 32. Sample image from DeepForest

Figure 32. Sample image from Parrot Bebop, Sierra Fria pine forest, Mexico

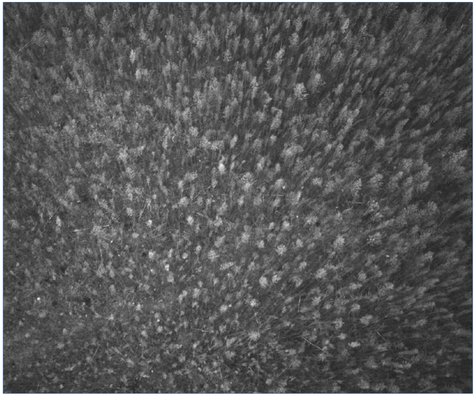

Figure 33. Red band from Altum

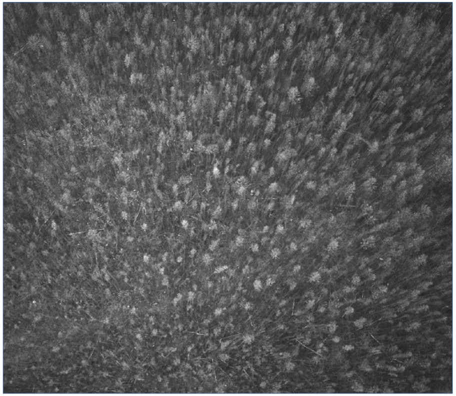

Figure 34. Green band from Altum

Data Set Overview

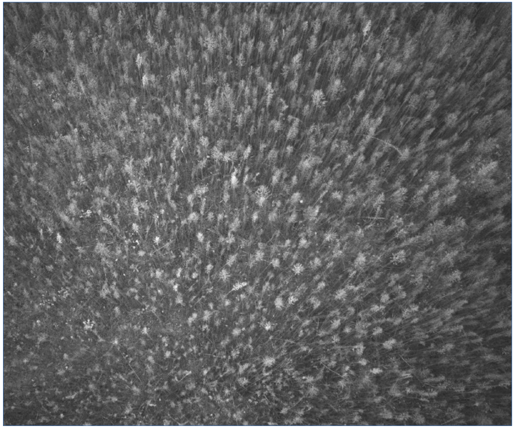

Figure 35. Red edge band from Altum

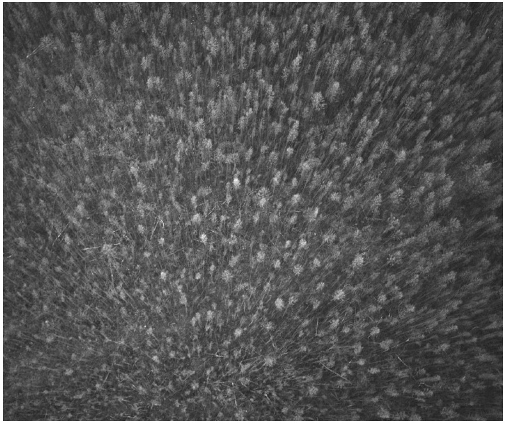

Figure 36. Blue band from Altum

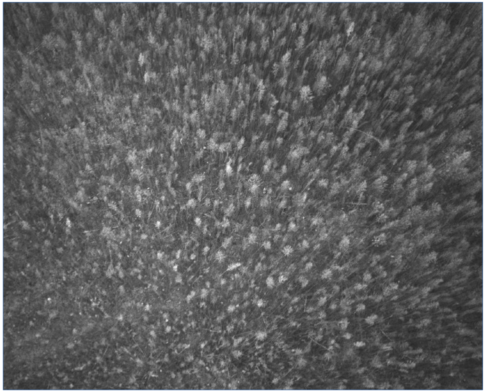

Figure 37. NIR band from Altum

DNN Architecture

- Input – multispectral image.
- Location of trees – 2D confidence map modeling.
- Pyramid pooling method will be used to improve the confidence map estimation.
- Feature map extraction – VGG16.
- 8 convolutional layers

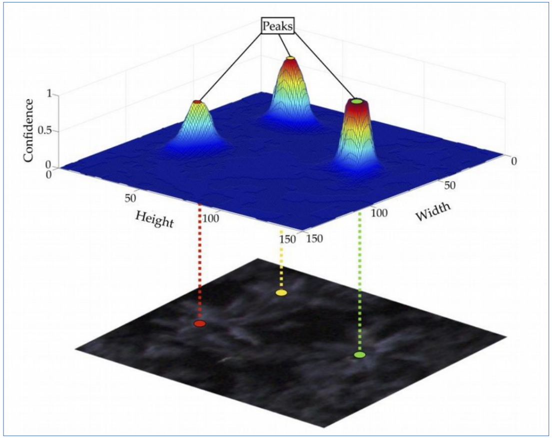

Figure 38. Tree localization from confidence map

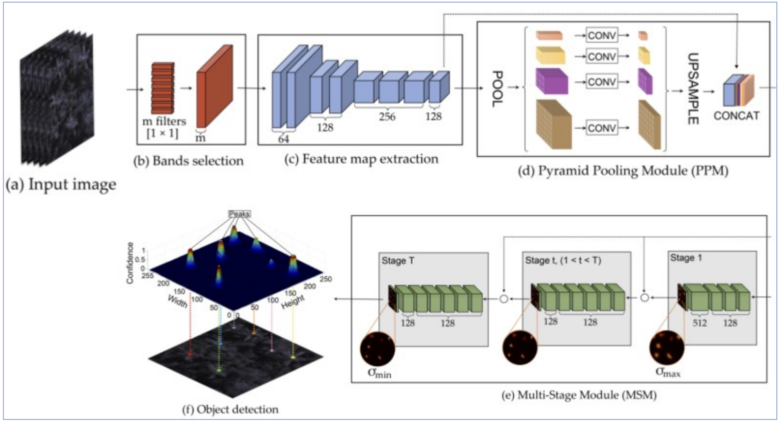

Figure 39. Proposed DNN Architecture

Conclusion

- Environmental challenges in 21st century are trans-disciplinary.
- This projects seeks collaborative research between Science and Engineering.
- Employ a custom UAV with state of the art sensors.
- Map ecological dynamics of a forest landscape and model the system.
- This work will be expanded to a heterogeneous team of UAVs and UGVs.
- Applications – Forestry, Agroindustry, Green technology startups, etc.

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Thank You