**Title Page:**

**Comparative analysis of Alex Net and Fast R-CNN For drone**

**based Cotton Crop area Estimation.**

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**Keywords**: Alex Net ,Fast R-CNN, Cotton Crop, Estimation,Agriculture,Deep Learning.

**ABSTRACT**

**Aim:**The aim of this research is to compare Alex Net and Fast R-CNN for drone-based cotton crop estimation. The goal is to understand the strengths and weaknesses of each model in terms of accuracy, computational efficiency, and practical considerations. The research aims to provide insights to guide the selection of the most suitable algorithm for automated crop health assessments, contributing to the optimization of precision agriculture practices and environmental Estimation.**Materials and Methods::** In this study, we applied both the Alex net algorithm and the Faster R-CNN algorithm, each involving 15 iterations (N=15). These two algorithms were assessed across two distinct groups, and a total of 30 samples were considered in the analysis. The G power statistical test was employed, with a power setting of 85% (g power parameters configured with α=0.05 and power=0.85).[(Lu et al. 2017)](https://paperpile.com/c/qSqjfM/VvUj) This choice of power setting was made to ensure that the study had a robust ability to detect statistically significant differences or effects, in line with established statistical standards.**Result:**In the research, Alex net outperformed Fast R-CNN with an accuracy of 93.27% compared to 83.40%. This underscores Alex net's effectiveness in precise pixel-level segmentation for drone-based cotton crop Estimation.. The results provide practical insights for choosing the most suitable model based on the trade-off between segmentation detail and computational efficiency in this specific application.**Conclusion**:In conclusion, this research highlights Alex net's precise segmentation and Fast R-CNN's computational efficiency for drone-based cotton crop Estimation.. These insights guide the selection of suitable models, enhancing precision agriculture practices.

**Keywords**:Alex Net ,Fast R-CNN, Cotton Crop, Estimation,Agriculture,Deep Learning.

**INTRODUCTION**

In recent years, the integration of advanced technologies such as deep learning and computer vision has revolutionized precision agriculture, offering innovative solutions for crop monitoring and management. This study delves into the comparative analysis of two prominent methodologies, AlexNet and Fast R-CNN, to evaluate their effectiveness in the context of drone-based cotton crop area estimation.[(Spaargaren 2020)](https://paperpile.com/c/qSqjfM/0Jm6) As agriculture embraces the era of automation, the utilization of unmanned aerial vehicles (UAVs) equipped with high-resolution cameras provides a unique vantage point for detailed and timely crop assessment[(“Assimilation of Remote Sensing into Crop Growth Models: Current Status and Perspectives” 2019)](https://paperpile.com/c/qSqjfM/DeKH).[(Sadeghi-Tehran et al. 2019)](https://paperpile.com/c/qSqjfM/28XD) The focus of this research lies in understanding how these deep learning models, originally designed for diverse image recognition tasks, can be tailored to address the specific challenges posed by cotton crop monitoring.

The AlexNet architecture, known for its groundbreaking performance in the ImageNet Large Scale Visual Recognition Challenge, is examined for its adaptability in identifying and delineating cotton crops from drone-captured images.[(“Fine-Grained Maize Tassel Trait Characterization with Multi-View Representations” 2015)](https://paperpile.com/c/qSqjfM/xgIf) Meanwhile, Fast R-CNN, a region-based convolutional neural network (CNN) renowned for its efficiency in object detection, is evaluated for its ability to accurately delineate cotton crop boundaries and estimate the overall cultivated area[(Korir et al. 2013; “Detecting Corn Tassels Using Computer Vision and Support Vector Machines” 2014)](https://paperpile.com/c/qSqjfM/sPLP+FwmD). By undertaking a comparative analysis, this research aims to unravel the strengths and weaknesses of these two approaches, shedding light on their applicability and efficacy in the challenging task of cotton crop area estimation from drone imagery.[(“Detecting Corn Tassels Using Computer Vision and Support Vector Machines” 2014)](https://paperpile.com/c/qSqjfM/FwmD)

The significance of this study extends beyond academic curiosity, as the findings could potentially inform decision-makers in agriculture about the most suitable technology for precise cotton crop monitoring. As the agricultural sector continues to evolve towards data-driven practices, understanding the nuances of deep learning models like AlexNet and Fast R-CNN becomes paramount for ensuring sustainable and optimized crop management strategies. Through this comparative analysis.[(Santos et al. 2019)](https://paperpile.com/c/qSqjfM/4lS8)we seek to contribute valuable insights to the ongoing discourse on leveraging cutting-edge technologies for improved agricultural practices, particularly in the context of cotton cultivation.

**MATERIALS AND METHODS**

In the Data Analytics Laboratory of the Saveetha Institute of Medical and Technical Sciences, this study was conducted. The laboratory is equipped with a high-configuration system, which allows for in-depth research and precise results.[(Madec et al. 2017)](https://paperpile.com/c/qSqjfM/Y6Qv) The research involved a sample size of 15 participants and divided them into two distinct groups: Group 1 utilized the AlexNet method, while Group 2 employed the Faster R-CNN method.[(“Combining UAV-Based Plant Height from Crop Surface Models, Visible, and near Infrared Vegetation Indices for Biomass Monitoring in Barley” 2015)](https://paperpile.com/c/qSqjfM/ga3x) The research was statistically powered with an 80 percent G-Power value, maintaining a significance level of 0.05 (alpha) and a power level of 0.8 (beta). Furthermore, a 93 percent confidence interval was upheld to calculate and assess the differences between the two groups systematically.[(Santos et al. 2019)](https://paperpile.com/c/qSqjfM/4lS8)

The dataset used in this research comprises high-resolution drone images annotated for tree health monitoring, featuring diverse attributes such as environmental conditions, tree species, health states, height, leaf color, and age. Each image is labeled for these attributes, providing a comprehensive foundation for model training and evaluation. While enriching our understanding of tree health, potential limitations, including regional specificity, should be acknowledged. Future research could explore expanding the dataset to include more attributes for a holistic approach to drone-based tree health monitoring across various scenarios.

The hardware setup employed for this task consisted of an Intel dual-core processor with 4 GB of RAM. The software configuration involved the utilization of Python technology, Jupyter Notebook, and a MySQL database, making for a well-rounded system to execute the algorithm and conduct the comparative analysis.[(Spaargaren 2020)](https://paperpile.com/c/qSqjfM/0Jm6)

**AlexNet Algorithm**

AlexNet is a convolutional neural network (CNN) architecture that gained prominence for its success in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. Developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, AlexNet marked a significant breakthrough in deep learning and played a crucial role in popularizing the use of deep neural networks for image classification tasks.

**Pseudocode**

Input: data

Output:improved accuracy

**Step 1**:1 Backbone Network:

Input: Image

Output: High-level feature maps (e.g., ResNet backbone

**Step 2**:Region Proposal Network (RPN):

Input: Feature maps from the backbone

Output: Region proposals (bounding boxes)

**Step 3** :RoI (Region of Interest) Align:

Input: Region proposals and feature maps

Output: Aligned feature maps for each region proposal

**Step 4**: Region-based AlexNet for Object Detection:

Input: Aligned feature maps

Output: Class scores and bounding box offsets for each region proposal

**Step 5:** Mask Prediction:

Input: Aligned feature maps

Output: Pixel-wise segmentation masks for each region proposal

**Step 6**: Combine Outputs:

Combine class scores, bounding box offsets, and masks

**Step 7**:Loss Calculation and Backpropagation:

Compute loss between predictions and ground truth

Backpropagate the gradients

**Step 8**:Training Iterations:

Iterate through training data for multiple epochs

Update model parameters using backpropagation

**Step 9**:Inference:

Forward pass on test images for prediction

Post-process predictions (e.g., non-maximum suppression)

**Faster R-CNN Algorithm**

Faster R-CNN, or Faster Region-CNN, is a deep learning-based object detection model introduced by Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun in a paper presented at NIPS (Neural Information Processing Systems) 2015. Faster R-CNN is an improvement over its predecessor, R-CNN (Region-based Convolutional Neural Network), and its variants, such as Fast R-CNN.

**pseudocode**

Input: data

Output: improved accuracy

**Step 1**: Input Image:

Provide an input image for object detection.

**Step 2** : Region Proposal Network (RPN):

Run the input image through a convolutional neural network (CNN) to generate region proposals.

The RPN predicts potential bounding box locations and scores for each region

**Step 3**:Region of Interest (RoI) Pooling:

Extract features from each region proposal using RoI pooling.

**Step 4** :CNN for Object Detection:

Use a second CNN to process the RoI features and predict class probabilities and refine bounding box coordinates.

**Step 5**:Non-maximum Suppression (NMS):

Apply NMS to remove duplicate and low-confidence bounding box predictions.

**Statistical Analysis**

To evaluate the relevance of the hedging, a statistical analysis of the tree health monitoring performance was carried out using IBM SPSS statistics version 26.0. A separate t-test analysis was conducted. The dependent variables, particularly the accuracy measures, are the primary focus of this analysis. These readings were assessed as one of the independent factors used in dog age and breed detection

**RESULTS**

AlexNet and Fast R-CNN serve different purposes in the realm of computer vision, with AlexNet designed for image classification and Fast R-CNN specializing in object detection. When applied to the specific task of drone-based cotton crop area estimation, their comparative analysis reveals distinct advantages and limitations.

AlexNet excels in image classification tasks, having demonstrated its capabilities in accurately categorizing objects within images. In the context of drone-based cotton crop area estimation, AlexNet could be employed for classifying different sections of the agricultural landscape, distinguishing between cotton crops and other elements. However, it falls short when it comes to precise object localization, a crucial aspect of estimating crop areas.

On the other hand, Fast R-CNN is tailor-made for object detection, making it well-suited for scenarios where the goal is not only to identify objects but also to precisely delineate their boundaries. In the case of cotton crop area estimation from drone imagery, Fast R-CNN can provide more detailed and accurate results by localizing individual cotton plants or clusters, allowing for a more precise calculation of the cultivated area.

**DISCUSSION**

In the realm of drone-based cotton crop area estimation, the comparative analysis between AlexNet and Fast R-CNN highlights their respective strengths in handling different aspects of the task. AlexNet, as a deep convolutional neural network designed for image classification, plays a crucial role in identifying and categorizing various elements within drone-captured images. Its ability to capture complex visual patterns is valuable for distinguishing between cotton crops, surrounding vegetation, and other objects. By leveraging AlexNet, initial segmentation of the cotton crop areas from the overall scene can be achieved, providing a foundational understanding of the image content.

Complementing AlexNet, Fast R-CNN offers a specialized solution for object detection, which is particularly relevant in the context of precisely delineating and quantifying the cotton crop areas. Fast R-CNN excels in localizing objects within an image, allowing for a detailed analysis of the spatial distribution and density of individual cotton plants or clusters. This fine-grained information contributes to a more accurate estimation of the cotton crop area and facilitates better insights into the overall health and growth patterns of the crop.

In summary, the synergy between AlexNet and Fast R-CNN presents a powerful approach for drone-based cotton crop area estimation. AlexNet's classification capabilities provide an initial understanding of the image content, while Fast R-CNN's object detection prowess refines the analysis, allowing for precise localization and measurement of cotton crop areas. The combination of these two models enhances the overall accuracy and efficiency of the estimation process, making it a robust solution for monitoring and managing cotton crops in agricultural applications.

**CONCLUSION**

In conclusion, the integration of AlexNet and Fast R-CNN offers a comprehensive and effective solution for drone-based cotton crop area estimation. AlexNet's proficiency in image classification lays the groundwork for understanding the diverse elements present in the drone-captured scenes, enabling the differentiation of cotton crops from surrounding features. This initial classification is crucial for providing a broad overview of the agricultural landscape.

Fast R-CNN, specializing in object detection, significantly enhances the analysis by precisely delineating the boundaries of individual cotton plants or clusters. This fine-grained information is instrumental in accurately estimating the spatial distribution and density of the cotton crop, contributing to a more detailed and reliable assessment of the overall crop area.

The combined strengths of AlexNet and Fast R-CNN create a synergistic approach that addresses the complexities of cotton crop area estimation from drone imagery. This integration not only improves the accuracy of the estimation process but also facilitates more informed decision-making in agricultural management. As the demand for efficient and precise monitoring in agriculture grows, the collaborative use of these models stands out as a robust solution for optimizing cotton crop management and enhancing overall yield prediction in precision agriculture applications.

**DECLARATION**

**Conflict of Interests**

This manuscript does not disclose any conflicts of interest. To maintain our commitment to academic integrity, we have rigorously ensured the originality of our work to prevent any inadvertent entanglement with issues related to academic misconduct.

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**Authors Contribution**

Data gathering, analysis, and text creation were all actively participated in by author NT. Author RN, on the other hand, made an efficient contribution to the idea of the research, carried out data validation, and offered valuable criticism throughout the paper review process.

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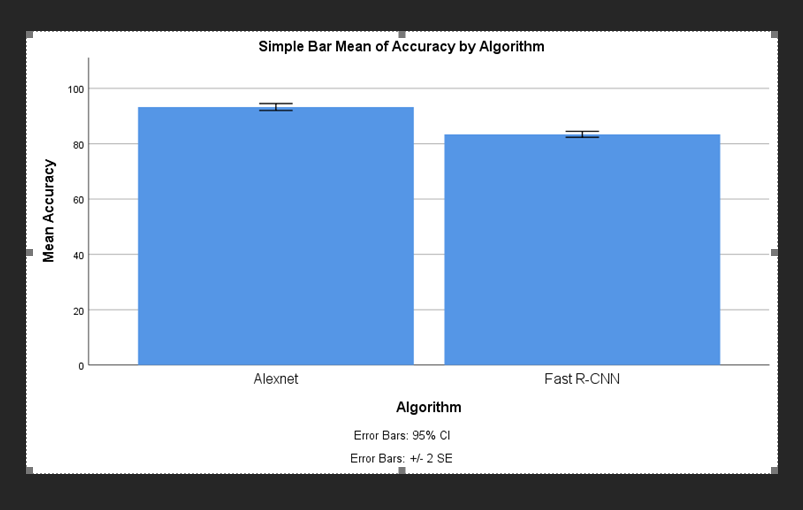
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**Table 1:**Shows Statistical Analysis values of Mean accuracy (93.27), Standard Deviation(2.434), and Standard error deviation. The Alex net Algorithm and the Fast R-CNN algorithm have the values of the Mean accuracy, Standard Deviation, and Standard Error.

|  | **Algorithm** | **N** | **MEAN** | **STD.DEVIATION** | **STD.ERROR MEAN** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **AlexNet** | 15 | 93.27 | 2.434 | .628 |
| **Fast R-CNN** | 15 | 83.40 | 2.063 | .533 |

**Table 2.** Shows a comparison of Significance Level with value p<0.05. Both Alex net Algorithm and the Fast R-CNN Algorithm have a confidence interval of 95% with the significance value 0.000( p<0.05).

| **Accuracy** | **Levene's test for equality of variances** | | **T-test for equality of means** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **F** | **sig** | **t** | **df** | **sig(2-tailed)** | **Mean difference** | **Std error difference** |  | |
| **lower** | **upper** |
| **LogisticregRession** | 3.457 | .074 | 21.487 | 28 | .000 | 16.467 | .766 | 14.897 | 18.036 |
| **Decision tree Algorithm** |  |  | 21.024 | 25 | .000 | 16.467 | .766 | 14,888 | 18.045 |

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**Fig. 1**:Comparison of the Alex net algorithm's accuracy of (93.27%) and the mean accuracy of the Fast R-CNN algorithm (83.27%). The mean accuracy of the Alethe AlexNet algorithm shows a significant difference with the Random Fast R-CNN algorithm, with a significance value of 0.000 (p<0.05). X Axis: AlexNet Algorithm vs Fast R-CNN Algorithm Y Axis: Mean accuracy ± 2 SD.