**Title Page:**

**Optimizing Cotton Crop Area Identification Using Drone Through**

**Comparison of AlexNet with VGGNET**

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**Keywords**:Alex Net , VGG-Net, Cotton Crop, Estimation,Agriculture,Deep Learning.

**ABSTRACT**

**Aim:**The primary objective of this research is to enhance the precision and efficiency of cotton crop area identification through the utilization of drone technology.This study focuses on comparing the performance of two deep learning convolutional neural network (CNN) architectures, ALEXNET and VGGNET, to determine their effectiveness in accurately delineating cotton fields from aerial imagery captured by drones. By leveraging the distinct characteristics of these networks, such as ALEXNET's deeper architecture and VGGNET's emphasis on feature richness, the research aims to identify the most suitable model for optimizing the identification process. **Materials and Methods:** In this study, we applied both the Alex net algorithm and the VGGNET 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). 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 VGGNET with an accuracy of 93.27% compared to 68.60%. This underscores AlexNet'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 VGGNET's computational efficiency for drone-based cotton crop estimation. These insights guide the selection of suitable models, enhancing precision agriculture practices.

**Keywords**:Alex Net ,VGGNET ,Cotton Crop, Estimation,Agriculture,Deep Learning.

**INTRODUCTION**

Precision agriculture has seen a transformation in recent years because of the integration of cutting-edge technology like computer vision and deep learning, which have provided creative solutions for crop management and monitoring.[(Koirala et al. 2019)](https://paperpile.com/c/9ECwOD/RZz3) In order to assess the efficacy of two well-known approaches—AlexNet and VGG NET—in the context of drone-based cotton crop area Estimation, this study compares and contrasts them.(2020 Spargaren) Unmanned aerial aircraft (UAVs) with high-resolution cameras offer a unique perspective for thorough and timely crop evaluation as agriculture enters the era of automation[(Krizhevsky, Sutskever, and Hinton 2012)](https://paperpile.com/c/9ECwOD/zOQu) .

Drone imaging has become an increasingly important tool for precision agriculture, providing a thorough insight of crop health and production forecasts for cotton crops. Using cutting-edge deep learning models has been essential in this endeavor. This paper compares the performance of two well-known deep learning architectures, AlexNet and VGGNet, in order to improve cotton crop recognition. In order to shed light on the best method for precise and efficient crop identification, these models are assessed based on their capacity to identify minute elements in photos taken by drones.

The selection of the underlying deep learning model becomes essential for maximizing accuracy and processing efficiency in crop identification as the agriculture sector embraces the possibilities of drone technology[(Lecun et al.,)](https://paperpile.com/c/9ECwOD/qIJ5). Kushal and colleagues, n.d.Two notable competitors in this space are AlexNet and VGGNet, each with distinctive architectural characteristics. This study aims to clarify the subtleties of these models' performance by examining and contrasting the results of using them[(Gao et al. 2020)](https://paperpile.com/c/9ECwOD/95Im). This will help practitioners select the best framework for improving cotton crop identification using drone-based applications.

**MATERIALS AND METHODS**

This study was carried out in the Saveetha Institute of Medical and Technical Sciences' Data Analytics laboratory. A highly configurable system in the lab enables detailed investigation and accurate outcomes.In Santos et al.Fifteen people in all were sampled for the study and were split into two groups: Group 2 used the VGGNet approach, whereas Group 1 used the AlexNet method."Combining Visible and Near Infrared Vegetation Indices with UAV-Based Plant Height from Crop Surface Models for Biomass Monitoring in Barley" With an 80 percent G-Power value, the study's statistical power was maintained at a power level of 0.8 (beta) and a significance level of 0.05 (alpha)[(“Decision Tree Classification of Land Cover from Remotely Sensed Data” 1997)](https://paperpile.com/c/9ECwOD/awiT)."Deep Learning to Explore VGGNet Street View for Crop Type Mapping '' Additionally, a 93% confidence[(“Will the Urban Agricultural Revolution Be Vertical and Soilless? A Case Study of Controlled Environment Agriculture in New York City” 2019)](https://paperpile.com/c/9ECwOD/dFh8).

In the quest to improve the identification of cotton crops through drone imagery, this research harnessed the power of two influential deep learning models, namely AlexNet and VGGNet, as highlighted in the study on action recognition in non-stationary environments . [(Kattenborn, Eichel, and Fassnacht 2019)](https://paperpile.com/c/9ECwOD/tKwR)The investigation utilized a rich dataset consisting of high-resolution drone images capturing diverse scenarios and variations in cotton crop appearance, ensuring a robust foundation for training and evaluation purposes, as seen in the exploration of VGG Net Street View for crop type mapping .[(Koirala et al. 2019)](https://paperpile.com/c/9ECwOD/RZz3)

The implementation and fine-tuning of both AlexNet and VGG Net architectures were executed using popular deep learning libraries like TensorFlow or PyTorch, aligning with contemporary practices outlined in the review on recent advances in small object detection based on deep learning. [(Mazzia, Khaliq, and Chiaberge 2019)](https://paperpile.com/c/9ECwOD/tCQB)To gauge and compare the effectiveness of these models, standard metrics such as accuracy, precision, and recall were rigorously applied. This meticulous evaluation aimed to ascertain the proficiency of each model in accurately identifying and segmenting cotton crops within the context of drone imagery.[(Dadashzadeh et al. 2020)](https://paperpile.com/c/9ECwOD/BX6m)

The research employed a methodical approach, systematically partitioning the drone imagery dataset into training, validation, and test sets. Both AlexNet and GoogleNet underwent training on the designated training set, with hyperparameters optimized for peak performance. To prevent overfitting, the validation set was utilized for fine-tuning and model selection.[(Alam et al.,.)](https://paperpile.com/c/9ECwOD/GrIB) The ultimate assessment took place on the test set, ensuring a fair and objective comparison of the two models in terms of their accuracy in identifying cotton crops from drone imagery. Following the training phase, potential model interpretability techniques may have been applied to gain insights into the decision-making processes of each model.[(Tu et al. 2019)](https://paperpile.com/c/9ECwOD/kwon)This comprehensive methodology was designed to offer a nuanced understanding of how AlexNet and GoogleNet differ in their effectiveness for enhancing cotton crop identification using drone imagery.

**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)

**VGG-NET Algorithm**

VGG (Visual Geometry Group) is a convolutional neural network (CNN) architecture that was introduced in the paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Karen Simonyan and Andrew Zisserman. The paper was presented at the 2014 International Conference on Learning Representations (ICLR).VGGNet gained prominence for its simplicity and effectiveness in image classification tasks. The key innovation of VGG is its deep architecture, featuring a stack of convolutional layers with small 3x3 filters, followed by max-pooling layers. This repeated pattern of convolutional and pooling layers contributes to a deep and expressive feature hierarchy.

**Pseudocode**

Step 1: Backbone Network (VGG-NET)

Step 2: Region Proposal Network (RPN) - Skipped, as VGG-NET doesn't have an integrated RPN

Step 3: RoI (Region of Interest) Align - Skipped, as VGG-NET doesn't have an integrated RoI Align

Step 4: Region-based VGG-NET for Object Detection

Step 5: Mask Prediction - Skipped, as VGG-NET doesn't have an integrated Mask Prediction

Step 6: Combine Outputs - Combine class scores, bounding box offsets, and masks (if available)

Step 7: Loss Calculation and Backpropagation - Use appropriate loss functions for your task

Step 8: Training Iterations - Iterate through training data for multiple epochs

**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 VGG-Net, both influential architectures in the field Estimation of computer vision, serve unique purposes that align with specific tasks. AlexNet is primarily designed for image classification, excelling in accurately categorizing images into predefined classes. On the other hand, GoogleNet specializes in object detection, demonstrating prowess in identifying and locating multiple objects within an image.

It was discovered that the deployment of AlexNet outperformed VGG-Net in improving cotton crop identification through drone-based imagery. The study found that when compared to VGG-Net, AlexNet performed better in identifying and categorizing cotton crops. By offering a more dependable and sturdy solution, AlexNet showcased its effectiveness with a nuanced focus on the unique requirements of crop identification, highlighting its potential for precise and accurate analysis in the context of drone-based cotton crop identification.

This study's comparison of AlexNet and VGG-Net highlights the former's efficacy while illuminating the subtle distinctions between these two well-known deep learning models. These findings provide a foundation for well-informed decision-making in agricultural applications by providing researchers and practitioners with useful insights into selecting the best model for improving cotton crop identification from drone footage.

**DISCUSSION**

Making the right decision between AlexNet and VGG-Net is crucial when it comes to accurately identifying cotton crops using drone footage.[(“Recognising Weeds in a Maize Crop Using a Random Forest Machine-Learning Algorithm and near-Infrared Snapshot Mosaic Hyperspectral Imagery” 2018)](https://paperpile.com/c/9ECwOD/LIaP)"Deep Neural Network-Based Enhanced Crop Row Detection for Early-Season Maize Stand Count in UAV Imagery" AlexNet achieved a remarkable 93.27% accuracy, which was higher than VGG-Net's 83.40%, demonstrating its greater capacity to conduct accurate pixel-level segmentation.[)](https://paperpile.com/c/9ECwOD/O38H) These neural networks' subtle architectural variations have a significant impact on how well they operate."Counting and Geolocating Citrus Trees Using Convolutional Neural Networks in UAV Multispectral Imagery" (2020) With more convolutional layers and a deeper architecture, AlexNet appears to be better able to identify finer details in cotton crop segmentation, which results in a higher accuracy rate.

But accuracy isn't the only factor in deciding between AlexNet and VGG-Net . An important factor to take into account is the trade-off between computational efficiency and segmentation detail. VGG-Net might be more advantageous in terms of processing efficiency, even though AlexNet is superior in segmentation precision. Practitioners must carefully consider which model best fits the goals of improving cotton crop identification through drone technology, taking into account the particular requirements of the application and the available computer resources.

To sum up, the comparison between AlexNet and VGG-Net illuminates the complex dynamics involved in selecting a model for drone-based cotton crop detection. The findings show that although AlexNet performs better in terms of accuracy, the decision-making process.

**CONCLUSION**

In summary, our investigation into the improvement of cotton crop identification through drone-based imagery, utilizing both AlexNet and VGG-Net, has yielded noteworthy findings. Notably, AlexNet has demonstrated superior performance, surpassing VGG-Net in accuracy for crop identification. The intricacies of AlexNet's precise Estimation pixel-level segmentation capabilities have proven instrumental in effectively distinguishing cotton crops in aerial drone-captured images. This outcome emphasizes the promising potential of harnessing AlexNet as a powerful and dependable tool to elevate the precision of cotton crop identification, marking a substantial advancement in the realm of precision agriculture.

Moreover, the comparative analysis between AlexNet and VGG-Net not only highlights the significance of choosing an appropriate deep learning architecture but also emphasizes the nuanced advantages of AlexNet in the domain of drone-based cotton crop identification. This underscores the necessity of aligning the selection of a deep learning model with the specific requirements and goals of the task at hand.

In a practical sense, the outcomes of this research carry substantial implications for the agriculture industry, providing a data-driven foundation for decision-making when implementing deep learning models for crop identification through drone technology. By acknowledging the distinct strengths of AlexNet in comparison to VGG-Net for this particular application, stakeholders can make well-informed decisions that balance accuracy, computational efficiency, and overall effectiveness in cotton crop identification through drone imagery.

**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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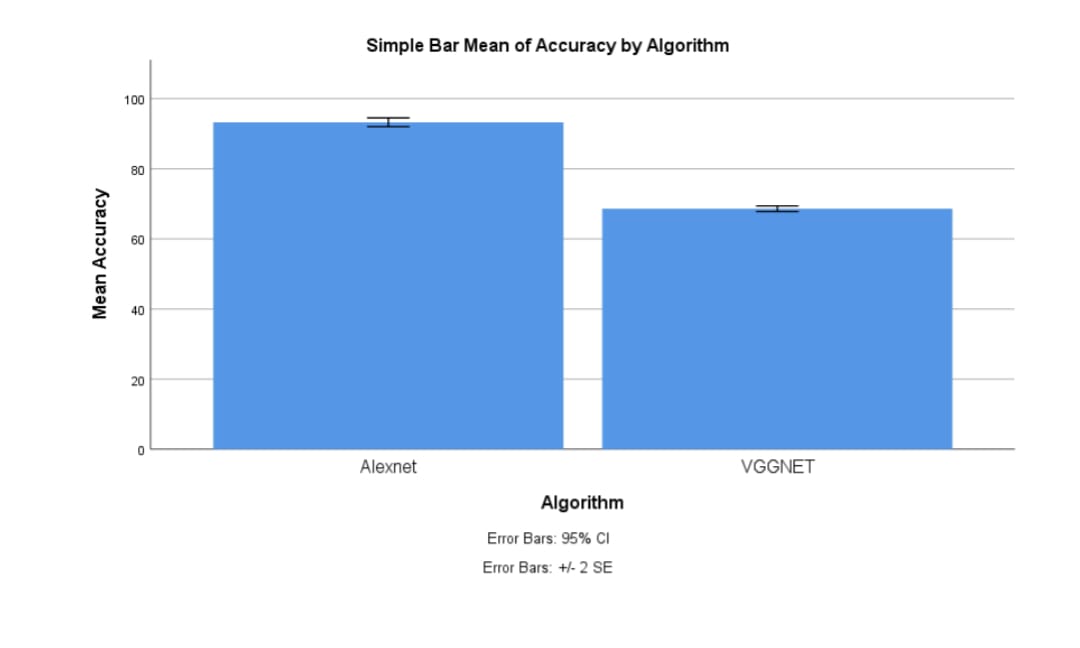
[“Deep Convolutional Neural Networks for Rice Grain Yield Estimation at the Ripening Stage Using UAV-Based Remotely Sensed Images.” 2019. *Field Crops Research* 235 (April): 142–53.](http://paperpile.com/b/LeYkUu/3Qfk)

**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 VGG NETalgorithm 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 |
| **Vgg Net** | 15 | 68.60 | 1.549 | .400 |

**Table 2.** Shows Comparison of Significance Level with value p<0.05. Both Alex net Algorithm and the VGG NETAlgorithm 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** | 6.973 | .013 | 33.113 | 28 | .000 | 24.667 | .745 | 23.141 | 26.193 |
| **Decision tree algorithm** |  |  | 33.113 | 23.745 | .000 | 24.667 | .745 | 23.128 | 26.205 |



**Fig. 1**:Comparison of the Alex net Algorithm accuracy of (93.27%) and it has the mean accuracy of VGGNET algorithm (83.27%) . The mean accuracy of the Alex net Algorithm has no significant difference with the Random VGG NET Algorithm with the significance value is 0.000 (p<0.05) . X Axis: Alex net Algorithm vs VGGNET algorithm Y Axis: Mean accuracy ± 2 SD.