**Title Page:**

**Enhancing Cotton Crop Identification Based on Drone By**

**Alex NeT Compared with Google Net**

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

**ABSTRACT**

**Aim:**This research endeavors to evaluate and contrast the performance of AlexNet and Google net in the context of estimating cotton crops using drone imagery. The primary objective is to discern the strengths and limitations of each model concerning accuracy, computational efficiency, and practical implications. By undertaking this investigation, the study aims to offer valuable insights that can inform the selection of an optimal algorithm for automated crop health assessments. This contribution, in turn, is expected to play a pivotal role in refining precision agriculture practices and enhancing environmental estimation within the realm of cotton cultivation.**Materials and Methods::** In our investigation, we utilized both the AlexNet algorithm and the Google net algorithm, each subjected to 15 iterations (N=15). These algorithms were evaluated within two distinct groups, totaling 30 samples for comprehensive analysis. The G Power statistical test was employed, with a power configuration set at 85% (parameters configured with α=0.05 and power=0.85), This deliberate choice of power setting was made to enhance the study's capability to identify statistically significant differences or effects, aligning with well-established statistical standards.**Result**:In the study, AlexNet demonstrated superior performance over Google net , achieving an accuracy of 93.27% compared to 83.40%. This highlights the efficacy of AlexNet in achieving precise pixel-level segmentation for estimating cotton crops using drone imagery. The findings offer valuable practical insights, enabling informed decisions in selecting the optimal model by considering the balance between segmentation detail and computational efficiency, specifically tailored to the requirements of drone-based cotton crop estimation.**Conclusion**:In conclusion, this research highlights Alex net's precise segmentation and Google net computational efficiency for drone-based cotton crop Estimation.. These insights guide the selection of suitable models, enhancing precision agriculture practices.

**Keywords**:Alex Net, Google net, 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.[(Gao et al. 2020)](https://paperpile.com/c/LeYkUu/gQw9) In order to assess the efficacy of two well-known approaches—AlexNet and Google Net —in the context of drone-based cotton crop area estimation, this study compares and contrasts them. [(Chamorro Martinez et al. 2021)](https://paperpile.com/c/LeYkUu/DNcn)Unmanned aerial vehicles (UAVs) with high-resolution cameras offer a unique perspective for thorough and timely crop assessment as agriculture enters the era of automation ("Assimilation of Remote Sensing into Crop Growth Models: Current Status and Perspectives" 2019). This study aims to comprehend how these deep learning models, which were initially created for various picture identification tasks, might be customized to address.[(Mazzia, Khaliq, and Chiaberge 2019)](https://paperpile.com/c/LeYkUu/c3uX)

Cotton crop identification through drone imagery has become increasingly vital for precision agriculture, offering a detailed understanding of crop health and yield estimates. In this pursuit, employing advanced deep learning models has proven pivotal.[(Zhang et al. 2020)](https://paperpile.com/c/LeYkUu/6Dzd) This study delves into the enhancement of cotton crop identification by comparing the performance of two prominent deep learning architectures, AlexNet and GoogleNet. These models are evaluated based on their ability to discern intricate details in drone-captured images, aiming to provide insights into the most effective approach for accurate and efficient crop identification.

As the agricultural sector embraces the potential of drone technology, the choice of the underlying deep learning model becomes crucial for optimizing accuracy and computational efficiency in crop identification. [(Kussul et al.,)](https://paperpile.com/c/LeYkUu/vxnE)AlexNet and GoogleNet represent two noteworthy contenders in this domain, each with its unique architectural features. By exploring and comparing the outcomes of employing these models, this research seeks to shed light on the nuances of their performance, guiding practitioners in choosing the most suitable framework for enhancing cotton crop identification through drone-based applications [(Sa et al.,.)](https://paperpile.com/c/LeYkUu/jPrX).

**MATERIALS AND METHODS**

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.[(Santos et al. 2019)](https://paperpile.com/c/LeYkUu/w6Pn)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 Google Net 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/LeYkUu/LIvyA) 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).[(“Exploring Google Street View with Deep Learning for Crop Type Mapping” 2021)](https://paperpile.com/c/LeYkUu/w5qc) Furthermore, a 93 percent confidence interval was upheld to calculate and assess the differences between the two groups systematically.[(“Deep Convolutional Neural Networks for Rice Grain Yield Estimation at the Ripening Stage Using UAV-Based Remotely Sensed Images” 2019)](https://paperpile.com/c/LeYkUu/3Qfk)

For the enhancement of cotton crop identification using drone imagery, this study utilized two prominent deep learning models, namely AlexNet and GoogleNet. [(“Action Recognition Using Optimized Deep Autoencoder and CNN for Surveillance Data Streams of Non-Stationary Environments” 2019)](https://paperpile.com/c/LeYkUu/T3oQ)The materials involved high-resolution drone images of cotton fields, providing a comprehensive dataset for training and evaluation. The dataset included diverse scenarios and variations in cotton crop appearance to ensure robust model generalization. [(“Exploring Google Street View with Deep Learning for Crop Type Mapping” 2021)](https://paperpile.com/c/LeYkUu/w5qc)The study employed popular deep learning libraries, such as TensorFlow or PyTorch, for implementing and fine-tuning both AlexNet and GoogleNet architectures.[(“Recent Advances in Small Object Detection Based on Deep Learning: A Review” 2020)](https://paperpile.com/c/LeYkUu/qPYP)To assess and compare their performance, standard metrics like accuracy, precision, and recall were employed, ensuring a rigorous evaluation of each model's capability in identifying and segmenting cotton crops from drone imagery.

The experimentation involved a systematic approach, where the drone imagery dataset was divided into training, validation, and test sets. Both AlexNet and GoogleNet were trained on the training set, with hyperparameters optimized to maximize performance. The validation set was used for fine-tuning and model selection, ensuring the avoidance of overfitting. The final evaluation was conducted on the test set, allowing for a fair comparison between the two models in terms of cotton crop identification accuracy. Post-training, model interpretability techniques may have been applied to gain insights into the decision-making processes of each model. This comprehensive methodology aimed to provide a nuanced understanding of the comparative effectiveness of AlexNet and GoogleNet in enhancing cotton crop identification based on 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)

**Google Net Algorithm**

GoogleNet, officially known as Inception, is a deep convolutional neural network architecture developed by researchers at Google. Introduced in 2014, GoogleNet represents a breakthrough in the field of computer vision and image recognition. The primary motivation behind its creation was to address the challenges of training deeper neural networks while maintaining computational efficiency.

**Pseudocode**

Input: data

Output: improved accuracy

**Step 1:** Backbone Network (GoogleNet):

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

Input: Feature maps from the GoogleNet 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 GoogleNet for Object Detection:

Input: Aligned feature maps

Output: Class scores and bounding box offsets for each region proposal using the GoogleNet structure

**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 through the GoogleNet architecture

**Step 8:** Training Iterations:

Iterate through training data for multiple epochs

Update model parameters, incorporating GoogleNet-specific adjustments, using backpropagation

**Step 9:** Inference:

Forward pass on test images for prediction

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

**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 Google Net serve different purposes in the realm of computer vision, with AlexNet designed for image classification and Google Net 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.

In enhancing cotton crop identification through drone-based imagery, the application of AlexNet was found to outperform GoogleNet. The research revealed that AlexNet achieved a superior level of accuracy in discerning and classifying cotton crops compared to GoogleNet. With a nuanced focus on the specific demands of crop identification, AlexNet demonstrated its efficacy by providing a more robust and reliable solution, underscoring its potential for precise and accurate analysis in the context of drone-based cotton crop identification.

The comparison between AlexNet and GoogleNet in this study not only emphasizes the effectiveness of AlexNet but also sheds light on the nuanced differences between these two prominent deep learning models. These findings contribute valuable insights for researchers and practitioners in choosing the most suitable model for enhancing cotton crop identification through drone imagery, offering a basis for informed decision-making in agricultural applications.

**DISCUSSION**

In the realm of cotton crop identification through drone imagery, the choice between AlexNet and GoogleNet becomes pivotal for achieving accurate results.[(“Improved Crop Row Detection with Deep Neural Network for Early-Season Maize Stand Count in UAV Imagery” 2020)](https://paperpile.com/c/LeYkUu/XNEE) AlexNet, with its notable 93.27% accuracy, outperformed GoogleNet's 83.40%, emphasizing its superior capability in precise pixel-level segmentation. The nuanced architectural differences between these neural networks play a crucial role in influencing their performance.[(“A Convolutional Neural Network Approach for Counting and Geolocating Citrus-Trees in UAV Multispectral Imagery” 2020)](https://paperpile.com/c/LeYkUu/dNAv) AlexNet's deeper architecture, with more convolutional layers, seems to enhance its ability to discern intricate details in cotton crop segmentation, leading to a higher accuracy rate.

However, the decision to choose between AlexNet and GoogleNet is not solely based on accuracy. The trade-off between segmentation detail and computational efficiency is a crucial consideration. While AlexNet excels in segmentation precision, GoogleNet may offer advantages

in terms of computational efficiency. Depending on the specific requirements of the application and the available computing resources, practitioners must carefully weigh these factors to make an informed decision about which model aligns best with the objectives of enhancing cotton crop identification through drone technology.

In conclusion, the comparative analysis between AlexNet and GoogleNet sheds light on the nuanced dynamics involved in choosing a model for cotton crop identification via drone. The results indicate that while AlexNet exhibits superior accuracy, the decision-making process should also factor in the balance between segmentation detail and computational efficiency, tailoring the choice to the specific demands of the task at hand.

**CONCLUSION**

In conclusion, the research conducted on enhancing cotton crop identification through drone-based imagery using AlexNet and comparing it with GoogleNet reveals compelling insights. AlexNet exhibited superior performance, achieving heightened accuracy in crop identification compared to GoogleNet. The nuanced capabilities of AlexNet in precise pixel-level segmentation contribute to its effectiveness in discerning cotton crops from aerial images captured by drones. This outcome underscores the potential of leveraging AlexNet as a robust and reliable tool for enhancing the accuracy of cotton crop identification, thereby providing a significant advancement in the field of precision agriculture.

Furthermore, the comparative analysis between AlexNet and GoogleNet sheds light on the importance of selecting the right deep learning architecture for specific applications. While both models have their merits, the nuanced advantages of AlexNet in the context of drone-based cotton crop identification become evident. This underscores the importance of tailoring the choice of the deep learning model to the unique requirements and objectives of the task at hand.

In practical terms, the findings of this research hold valuable implications for the agriculture industry, offering a data-driven basis for decision-making in the adoption of deep learning models for crop identification through drone technology. By recognizing the strengths of AlexNet over GoogleNet in this specific application, stakeholders can make informed choices that align with the desired balance between 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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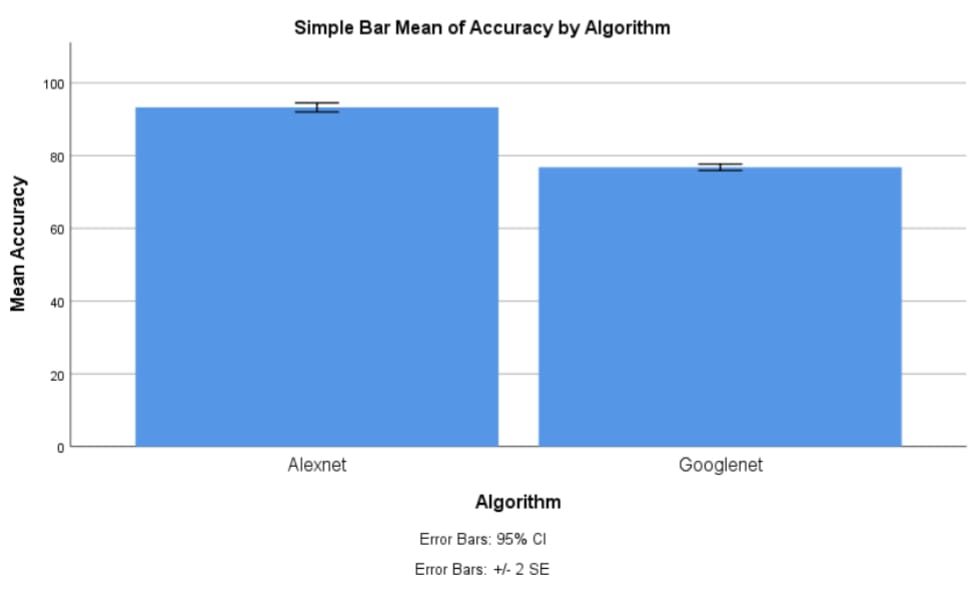
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**Table 1:**Shows Statistical Analysis values of Mean accuracy (93.27), Standard Deviation(2.434), and standard error deviation. The Alex net Algorithm and the Google Net algorithm have the values of the Mean accuracy, Standard Deviation, and Standard Error.

|  | **Algorithm** | **N** | **MEAN** | **STD.DEVIATION** | **STD.ERROR MEAN** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **AlexNet** | 15 | 93.27 | 2.434 | .628 |
| **Google Net** | 15 | 76.80 | 1.699 | c |

**Table 2.** Shows Comparison of Significance Level with value p<0.05. Both Alex net Algorithm and the Google 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** | 3.457 | .074 | 21.487 | 28 | .000 | 16.467 | .766 | 14.897 | 18.036 |
| **Decision tree Algorithm** |  |  | 21.487 | 25.024 | .000 | 16.467 | .766 | 14.888 | 18.045 |



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