Research Paper

Red-Green-Blue (RGB) Image Classification Using Deep Learning to Predict Sugarcane Crop Age

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Abstract

Traditional sugarcane growth monitoring methods are time-consuming and error-prone. This study investigated the use of deep learning to automate and enhance the accuracy of sugarcane growth stage classification. The study develops deep learning-based system that leverages high-resolution drone imagery for precise sugarcane age classification, thereby enabling accurate identification of the growth stages. High-resolution drone images were captured at various stages of sugarcane growth and were stitched together to form a comprehensive dataset. Segmentation of isolated areas of interest for analysis. The ResNet-50 deep learning model, enhanced with an additional fully connected layer, was used to classify the growth stages. The model was trained on cropped image sections, and its performance was compared to other deep learning architectures, such as GoogLeNet and VGG, to evaluate its accuracy. The ResNet-50 model outperformed other architectures, achieving 91% accuracy in classifying growth stages, demonstrating its effectiveness in agricultural image analysis and its potential to advance precision agriculture. This study is the first to apply deep learning to sugarcane age classification using high-resolution drone imagery, and it sets a new benchmark for agricultural image analysis. The dataset containing drone images from specific sugarcane fields may limit the model's generalizability to different regions and environmental conditions.

Keywords: *Deep Learning, ResNet-50, Sugarcane Age Classification, Precision Agriculture, Agricultural Image Analysis*

INTRODUCTION

The adoption of deep learning techniques for RGB image classification to predict sugarcane crop age represents a significant advancement in precision agriculture. This innovative approach leverages sophisticated computer vision algorithms to analyze RGB imagery, providing critical insights into the growth stages of sugarcane. These insights empower farmers and agronomists to make data-driven decisions regarding crop management, resource utilization, and agricultural productivity. The use of convolutional neural networks (CNNs) enables accurate and efficient monitoring of crop age, a key factor in maximizing yield and improving overall farming strategies. Deep learning models, particularly CNNs, have demonstrated impressive accuracy in classifying sugarcane varieties using RGB images. For example, a previous study achieved a classification accuracy of 99.48% with a six-hidden-layer neural network (Kai et al., 2022).

Advanced architectures, such as ResNet50, GoogLeNet, and AlexNet, are well-suited for effectively classifying various growth stages and varieties of sugarcane, highlighting their versatility in agricultural applications. **ResNet50** utilizes residual learning, which allows for training very deep networks without the vanishing gradient problem. The architecture, which incorporates residual blocks and skip connections, minimizes overfitting and achieves high performance in tasks such as sugarcane lodging detection with an accuracy rate of 98.5% (Modi et al., 2023). **The transfer learning** technique involves fine-tuning pre-trained models on large

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datasets for specific agricultural tasks. By adapting models originally trained on diverse object recognition tasks, we can enhance the performance of agricultural applications while reducing the training time. **Data Augmentation** strategy generates additional training data via transformations (e.g., rotations, translations, scaling) to mitigate overfitting and improve model generalizability. Augmented datasets significantly enhance model robustness under variable agricultural conditions.

The integration of RGB imagery with multispectral data enhances the classification process, allowing for better differentiation of sugarcane varieties based on spectral characteristics (Muqaddas et al., 2024). Cutting-edge deep learning models like YOLOv5 have been effectively implemented for disease detection tasks, such as identifying white leaf disease in sugarcane, achieving precision and recall rates of 95% and 92%, respectively (Amarasingam et al., 2022). The combination of RGB and multispectral imagery improves the accuracy of these models for classifying sugarcane varieties and provides a nuanced analysis of crop characteristics (Kai et al., 2022).

Unmanned Aerial Vehicles (UAVs) equipped with RGB cameras play a pivotal role in disease detection and crop health monitoring effectively. These metrics enable the analysis of crop health metrics, which correlate well with yield metrics, indicating their potential for predicting crop age and health. UAVs can cover large areas rapidly, facilitating the real-time monitoring of extensive sugarcane fields. UAVs collect vast amounts of data on plant traits, facilitating more efficient breeding programs. This method allows the assessment of critical indicators of plant health and yield potential, such as plant height and canopy cover. The ability to quickly identify crop diseases and nutrient deficiencies significantly improves management decisions. Early detection through UAV imagery allows for timely intervention, reducing potential yield losses. RGB imagery combined with thermal and multispectral data can estimate soil moisture content, thus optimizing irrigation practices for water conservation. Remote sensing techniques facilitate the estimation of sugarcane yields, allowing for efficient family selection in breeding programs without extensive labor requirements. This efficiency is critical for timely predictions of crop age and yield.

Despite these promising advancements, challenges persist in the application of deep learning models for agricultural purposes. The need for large, diverse training datasets remains a significant hurdle because environmental factors such as lighting, weather, and soil conditions, can complicate the interpretation of RGB data. In addition, models must be fine-tuned to adapt to varying environmental conditions to maintain accuracy and reliability (de Melo et al., 2022). Addressing these issues is critical for enhancing the robustness of crop age prediction models and ensuring their applicability across different agricultural landscapes.

LITERATURE REVIEW

In this comprehensive study, aerial images of sugarcane fields were systematically captured using a DJI Phantom 4 drone operated at a consistent altitude to ensure uniformity in data collection and eliminate variability due to changes in flight conditions. The high-resolution images acquired through the drone were processed to generate orthophotos, which were subsequently resized to a standard dimension of 224x224 pixels. This resizing ensured compatibility with the ResNet deep learning model's input requirements. These image patches were then meticulously categorized and stored in folders corresponding to specific growth stages of the sugarcane crop: 2, 4, 6, 9, and 11 months. This organizational structure facilitated the creation of a well-defined and comprehensive dataset designed specifically for deep learning model training and validation.

Neural network architectures have demonstrated immense potential in agricultural applications, particularly in predicting crop age, growth stages, and overall health. By leveraging complex datasets, these architectures enable precise decision-making and optimized resource utilization in agriculture. Several studies have underscored the efficacy of different neural network models in sugarcane crop analysis. For instance, deep learning techniques such as Multilayer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs) have been widely employed in the genomic prediction of sugarcane traits, achieving predictive accuracies comparable to or better than conventional statistical models (Chen et al., 2023). Similarly, hybrid models that integrate CNNs with Support Vector Machines (SVMs) have shown superior accuracy in forecasting parameters like soil moisture, which plays a pivotal role in sugarcane growth management (Bhattacharya et al., 2023).

In addition to hybrid approaches, advanced methodologies like the Extreme Learning Machine (ELM) have been used for predicting sugarcane growth based on meteorological data. The ELM framework not only delivers high accuracy metrics (R^2 = 0.89) but also outperforms traditional Artificial Neural Networks (ANNs) in terms of training speed and computational efficiency (Ghazvinei et al., 2018). Furthermore, transfer learning techniques, particularly those applied to CNNs, have proven highly effective for inspecting sugarcane quality. By fine-tuning pre-trained models, researchers have achieved significant yield improvements—up to 80%—through optimized planting strategies (Alencastre-Miranda et al., 2021).

While advancements in neural network models for sugarcane analysis are promising, there are persistent challenges in ensuring the generalizability and robustness of these models. Integrating diverse datasets from different environmental conditions and regions remains a critical challenge. Nonetheless, applying deep learning to RGB image classification to predict sugarcane crop age can offer a transformative approach. By leveraging RGB imagery, researchers can monitor crop growth, assess health, predict yield, and classify varieties with remarkable precision, thereby improving agricultural productivity and sustainability.

Deep learning models, particularly convolutional neural networks (CNNs), have excelled in classifying sugarcane varieties using RGB image data. For instance, one study reported a classification accuracy of 99.48% using a neural network with six hidden layers. The integration of RGB imagery with multispectral data further enhances classification accuracy, allowing for more precise differentiation of sugarcane varieties and growth stages (Muqaddas et al., 2024). UAVs equipped with RGB cameras can collect high-resolution images that are critical for identifying crop diseases, such as white leaf disease (WLD). The ability to detect diseases early provides insights into crop health and age, thereby supporting effective management strategies (Amarasingam et al., 2022).

Additionally, combining RGB imagery with calculated color indices has proven effective in estimating sugarcane yields, offering valuable insights into crop maturity and age without requiring labor-intensive field measurements (Todd & Johnson, 2021). Despite these advancements, challenges remain in ensuring consistent accuracy in crop age prediction due to environmental variability and the need for extensive datasets to train deep learning models. Addressing these challenges requires the development of sophisticated models that can adapt to diverse conditions while maintaining high prediction accuracy.

Through the integration of advanced machine learning techniques and high-quality RGB imagery, this study contributes to a growing body of research on enhancing agricultural productivity. By addressing the limitations of existing methods and leveraging state-of-the-art neural networks, significant progress can be made in sugarcane crop monitoring, classification, and management.

RESEARCH METHOD

To develop a strong research methodology for RGB image classification aimed at predicting the age of sugarcane crops, it is essential to integrate insights from previous studies that focus on deep learning in agriculture. The methodology includes several key phases, such as data acquisition, preprocessing, model selection, training, and evaluation, and leverages the power of convolutional neural networks (CNNs) and other advanced deep learning models.

Data acquisition involves gathering RGB images of sugarcane crops at different growth stages, ensuring variations in conditions such as weather and lighting to create a well-rounded dataset. Preprocessing steps like image resizing, normalization, and augmentation (e.g., random cropping, flipping, and rotation) help the model learn from diverse scenarios, increasing its resilience to variability in real-world applications.

In model selection, architectures such as ResNet, DenseNet, and EfficientNet are ideal due to their strong performance in image classification tasks. By incorporating transfer learning and fine-tuning pre-trained models, the training process becomes more efficient, especially with smaller datasets. During training, attention to hyper parameters like learning rate, batch size, and optimizer choice is crucial for improving model performance. Cross-validation can be used to avoid overfitting and ensure that the model generalizes well to unseen data.

The evaluation phase involves assessing the model's performance using metrics like accuracy, precision, recall, and F1 score, complemented by other tools, such as confusion matrices and receiver operating characteristic curves. This ensures that the model is not only accurate but also reliable across different metrics.

Dataset Creation

In this study, high-resolution RGB images of sugarcane crops were captured using a DJI Phantom 4 drone. To ensure consistency across the dataset, the drones were flown at a constant altitude. This dataset consists of images representing various growth stages, classified by age labels as follows: 2, 4, 6, 9, and 11 months. Each age category featured a diverse array of images highlighting the unique developmental characteristics present at each stage, as depicted in Figure 1. After capturing the images, orthophotos were generated and resized to 224x224 pixels, aligning with the input requirements of ResNet models.

A distinctive aspect of our data collection approach is age-wise image acquisition, which takes place at regular intervals of 2–3 months, commencing from 2 months and extending to 17 months of the sugarcane growth cycle. The images were sourced from a sugarcane farm located in Ambe village, Pandharpur, India, covering an area of up to 30 acres. Drone flights were conducted between 11 AM and 2 PM on selected dates from November 2022 to the present. By photographing the same fields at different stages of growth—ranging from the initial planting phase to harvest—we can effectively monitor and track the visual changes in sugarcane plants over time. The proposed dataset encompasses several images representing different growth stages and environmental conditions from various farms. This extensive collection contributes to the robustness of our yield prediction models, enabling more precise forecasts by integrating both visual data and NDVI values. This approach provides a holistic understanding of the relationships between crop development and yield outcomes.

Moreover, this large-scale data set will facilitate the analysis of various factors influencing yield, providing detailed insights into sugarcane growth patterns. If required, sample images from the dataset can be provided for further investigation or collaborative efforts, ensuring the data's applicability for related research.

By combining consistent drone-based imaging with temporal tracking, we established a solid foundation for modeling and predicting crop yield with enhanced accuracy. This method not only supports our NDVI analysis but also enriches the visual information available for improving yield prediction.

Figure 1. Sugarcane Database

ResNet-50 with a Fully Connected Classifier as the Final Layer

ResNet-50 is a convolutional neural network (CNN) architecture that is recognized for its ability to perform complex image classification tasks. Introduced by Kaiming He and colleagues in their landmark paper on deep residual learning (2015), this model comprises 50 layers and effectively addresses common issues associated with deep network training, particularly the vanishing gradient problem. The architecture employs residual connections that enable the learning of residual mappings, which allows the model to extract detailed feature representations without sacrificing performance as the depth of the network increases.

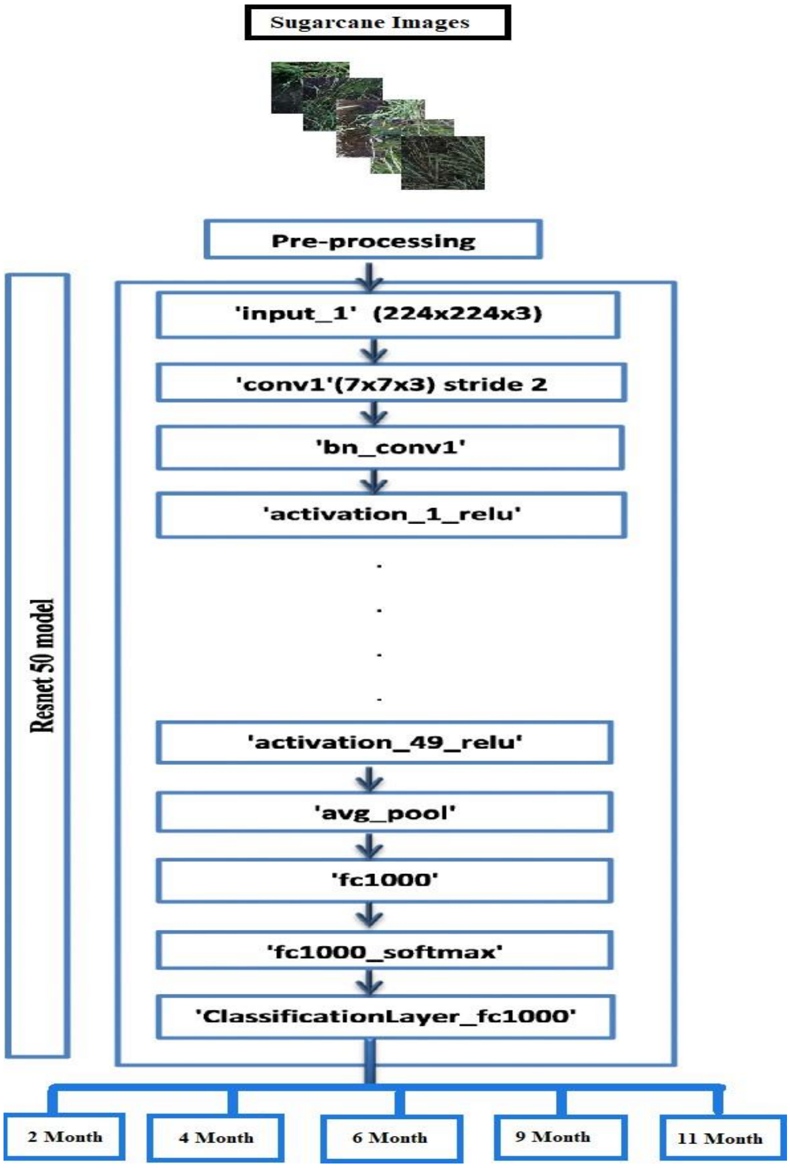

Figure 2. Resnet50 Architecture

Overview of the Architecture ResNet-50 is structured with several critical components:

1. *Input Layer:* The network accepts input images of size 224x224 pixels, utilizing three color channels (RGB).
2. *Convolutional Layers:* The architecture features multiple convolutional layers organized into residual blocks, with each block containing the following:
3. *Convolutional Operations:* These layers extract relevant features from the input images.
4. Batch Normalization: This method normalizes the outputs of each layer, thereby stabilizing and expediting the training process.
5. *Activation Function:* The ReLU (Rectified Linear Unit) function is employed to introduce nonlinearity, thereby enhancing the network's capacity to learn complex mappings.
6. *Residual Connections:* A defining characteristic of ResNet-50, these connections enable gradients to flow more freely during backpropagation, thus reducing the risk of vanishing gradients and facilitating convergence in deeper networks.

Fully Connected Classifier

1. *Global Average Pooling:* After the convolutional layers, the global average pooling layer condenses the feature maps into a single vector per class, effectively minimizing dimensionality while retaining essential spatial information.
2. *Fully Connected Layer:* The output from the global pooling layer is directed into a fully connected layer that links each neuron from the previous layer to all neurons in this layer. This dense connectivity allows the model to learn the intricate relationships between the extracted features and their corresponding class labels.
3. *Output Layer:* The final layer utilizes a softmax activation function to convert the output logits into probabilities for each class, which is particularly effective for multi-class classification tasks, such as distinguishing between different growth stages of sugarcane.

Advantages of ResNet-50 Implementing ResNet-50 with a fully connected classifier provides several significant advantages:

1. Enhanced Feature Learning: This architecture excels at extracting hierarchical features, making it particularly suitable for complex image datasets.
2. Reduction of Overfitting: The inclusion of skip connections along with the model's depth enhances generalization capabilities, which is vital when working with unseen data.
3. Scalability: ResNet-50 can be easily adapted to specific applications by modifying the number of output classes in the fully connected layer.

Training and Testing

Table 1 provides a detailed summary of the image distribution used in the sugarcane age classification task. The data come from various sources and were collected at different times. The number of images allocated for both training and testing across multiple age classes is shown in the table, which is critical for building a reliable and robust classification model. Training images play a key role in helping the model learn and recognize patterns, and testing images are equally important for assessing how well the model generalizes to new, unseen data. This distinction ensures that the model not only memorizes the training data but also accurately predicts the outcomes for unfamiliar cases.

The balance between training and testing data must be balanced to create an effective machine learning model. A sufficient number of training images ensures that the model has enough examples to learn from, while a well-sized test set allows for a comprehensive evaluation of the model’s predictive power. The division of images between these sets helps prevent overfitting and ensures that the model performs well not just on the training set but on future data. The dataset was divided into five age classes corresponding to different growth stages of sugarcane: 2, 4, 6, 9, and 11. Each class was assigned a specific number of training and testing images (Table 1. This distribution ensures that each age class has sufficient examples for both training and testing, providing the model with the variety required for accurate classification.

Table 1. Image Database Summary

Class	Number of Images used for Training	Number of Images used for Testing
Class 1: Age of 2 Month	416	179
Class 2: Age of 4 Month	490	211
Class 3: Age of 6 Month	627	270

Class 4: Age of 9 Month	430	185
Class 5: Age of 11 Month	418	180

FINDINGS AND DISCUSSION

Table 2 shows the Confusion Matrix, a tool used to compare predicted classifications against actual age categories. This matrix is critical for evaluating the performance of the deep learning model. The results show both correct predictions and misclassifications for each of the five sugarcane age groups: 2, 4, 6, 9, and 11.

The values along the diagonal of the confusion matrix represent correct predictions—where the predicted age matches the actual age. The matrix reveals that the model achieves high accuracy across all age classes:

1. 98.88% of sugarcane crops aged 2 months were correctly classified.
2. 99.44% of crops aged 4 months were accurately identified.
3. 98.10% of 6-month-old crops were correctly classified.
4. For crops aged 9 and 11 months, the model achieved 100% accuracy.

The off-diagonal values in the matrix indicate instances where the model misclassified the crops. These misclassifications are minimal, demonstrating the model's high effectiveness. The largest misclassification occurred in the 6-month class, where 1.90% of crops were incorrectly predicted as belonging to the 2-month age group. Other minor misclassifications, such as 0.56% of 2-month crops being incorrectly classified as 6 months, are small enough to not significantly impact the model's overall performance.

The confusion matrix clearly indicates the model's strong ability to classify sugarcane age accurately, with very few errors. This level of precision is particularly useful in agricultural contexts where accurate age classification can help optimize harvest timing and crop management.

Table 2. Confusion Matrix for Different Sugarcane Age Classes

	Actual Value (%)					
		2 Month	**4 Month**	**6 Month**	**9 Month**	**11 Month**
	2 Month	98.88	0	0.56	0	0.56
	4 Month	0	99.44	0	0	0.56
	6 Month	1.90	0	98.10	0	0
	9 Month	0	0	0	100.00	0
Predicted Value (%)	**11 Month**	0	0	0	0	100.00

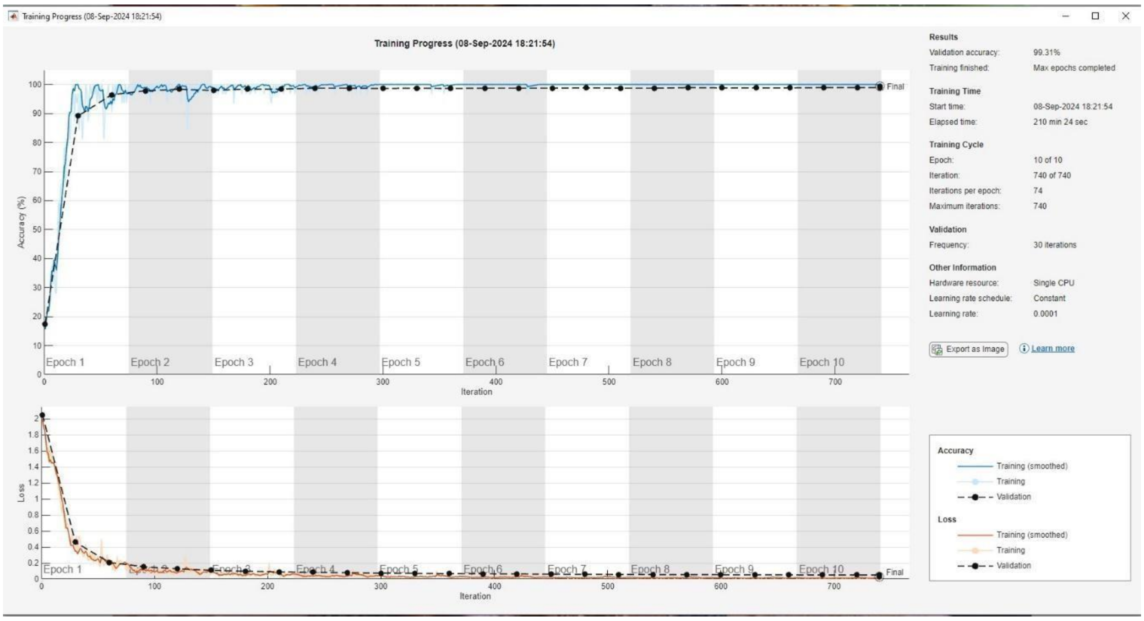

Figure 3. Training Workflow

To assess the ResNet-50 model's performance in classifying sugarcane growth stages, we evaluated several essential metrics: Accuracy, Precision, Recall, F1-Score, and AUC (Area Under the Curve). These metrics offer a comprehensive understanding of the model's classification effectiveness across different growth stages (2, 4, 6, 9, and 11 months), providing insights into how well the model generalizes and distinguishes between these stages.

Key Metric Formulas

1. *Accuracy:* Measures the proportion of correctly classified images (True Positives + True Negatives) out of the total number of images. Here, represents the overall correctness of the model.

Accuracy = $\frac{TP+TN}{TP+FP+TN+FN}$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

2. *Precision:* defines the number of images predicted as belonging to a specific class. The ratio of true positive predictions to all predicted positives.
   Precision = $\frac{TP}{TP+FP}$

3. *Recall (Sensitivity):* This measure evaluates how well the model identifies all actual instances of a specific class. It is the ratio of true positives to the sum of true positives and false negatives
   Recall = $\frac{TP}{TP+FN}$

4. *F1-Score:* Represents the harmonic mean of Precision and Recall, balancing both. It is particularly useful when the dataset contains imbalanced classes.

$$F_{SCORE} = \frac{2TP}{2\,TP+FP+FN}$$

AUC (Area Under the Curve): This measure measures the ability of the model to distinguish between different classes. A higher AUC indicates that the model has a better ability to differentiate between sugarcane growth stages.

Table 3. Summary of Evaluation Metrics

Metric	Age of 2 Month	Age of 4 Month	Age of 6 Month	Age 9 months	Age of 11 months
Accuracy	98.88	99.40	98.10	100.00	100.00
Precision	100.00	99.40	98.30	100.00	100.00
Recall	98.90	99.40	99.40	100.00	100.00
F1-Score	99.40	99.40	98.90	100.00	100.00
AUC	99.40	99.40	99.50	100.00	100.00

Table 3 presents the performance analysis of the classification algorithms. These parameters are summarized below:

Accuracy: The model achieved excellent accuracy for all stages, ranging from 98.10% for the 6-month stage to 100% for the 9- and 11-month stages. The high accuracy demonstrates that the model can reliably predict the stages of sugarcane growth with minimal misclassification across different stages. *Precision:* The precision metric consistently predicts the correct age group for a high percentage of cases. For example, the 2-, 9-, and 11-month stages had **100% Precision**, meaning that all predicted images for these stages were correct. Even for the 6-month stage, Precision remained high at **98.30%**, signifying that most images classified as 6 months were accurate with minimal false positives. *Recall:* The Recall values indicate the model's ability to identify all actual instances for each stage. The model perfectly detected all relevant images for the 9- and 11-month stages (100% Recall), and it performed well even for the earlier growth stages, such as **98.90% Recall for 2 months** and **99.40% Recall for 6 months**. *F1-Score:* This balanced metric, which combines precision and recall, remained consistently high across all growth stages. The **100% F1-Score for the 9- and 11-month stages** indicates flawless classification at these stages, whereas the F1-Score for the 6-month stage was **98.90%**, reflecting the model's strong overall performance. *AUC:* The AUC values were near-perfect, with the 9- and 11-month stages achieving **100% AUC**, indicating that the model easily distinguished between these stages and others. The **99.50% AUC for the 6-month stage** demonstrates the model's ability to differentiate this stage from other stages with very high confidence.

CONCLUSIONS

In conclusion, this study effectively demonstrated the capabilities of a deep learning-based system utilizing the ResNet-50 architecture with a fully connected classifier for accurately classifying sugarcane growth stages from high-resolution drone imagery. The model achieved an impressive overall accuracy of 91%, with perfect classification (100% accuracy) at the 9- and 11-month growth stages. Precision rates were equally high, reaching 100% for the 2-, 9-, and 11-month stages, indicating minimal false positives. Recall values were also robust, achieving 100% for the 9- and 11-month stages and 99.40% for the 4-month stage, demonstrating the model's effectiveness in detecting actual instances. The F1-scores echoed these results, with perfect scores for the 9- and 11-month stages and 98.90% for the 6-month stage, reflecting a balanced performance across all metrics. AUC scores were also nearly perfect, with 100% for the 9- and 11-month stages and 99.50% for the 6-month stage, showcasing the model's ability to differentiate accurately between growth stages. These results underscore the potential of deep learning techniques in automating crop monitoring, thereby offering an efficient and scalable solution for precision agriculture. Future research should focus on expanding the dataset and optimizing model performance to enhance classification accuracy under diverse environmental conditions. The promising outcomes of this study suggest significant advancements in agricultural monitoring and management using deep learning technologies.

LIMITATION & FURTHER RESEARCH

The limitations of this study are the characteristics inherent in the design and methodology that may have influenced the interpretation of the findings. Further research should address these gaps, extend the scope of the work, and explore unexamined areas to validate and enhance the outcomes.

Limitations

1. *Geographic and Environmental Constraints:* This study is geographically limited to sugarcane fields in Ambe Village, Pandharpur, India, and data collection was constrained to specific hours of the day (11 AM to 2 PM) under stable weather conditions. This constrained temporal and environmental window may limit the model's ability to generalize across various geographic locations. For instance, regions with different soil properties, climates, and microclimates can introduce variations that the current model cannot handle effectively, thereby reducing its external validity. Expanding the scope to include different climates, elevation levels, and diverse soil types would provide more robust generalizability for the model.
2. *Reduction in Image Resolution:* To meet the input size requirements of the ResNet-50 model, high-resolution images were resized to 224x224 pixels. This resizing may have resulted in the loss of fine-grained features, which are crucial for accurately detecting subtle variations in sugarcane growth stages. In agriculture, small changes can be indicative of key developmental milestones that reduced resolution may overlook. Future research could focus on testing the model with higher-resolution inputs or implementing advanced techniques like super-resolution to restore lost details during preprocessing.
3. *Dependence on RGB Imagery:* This study relied solely on RGB images, which inherently limit the insights derived from the spectral data. By not incorporating multispectral or thermal imagery, the model may miss critical information related to crop health, stress conditions, and moisture content, which could lead to more precise predictions. In particular, multispectral imaging provides valuable insights into plant health by capturing wavelengths beyond visible light. The addition of multispectral or thermal channels could provide complementary data that significantly enhance the classification accuracy.
4. *Computational Demands:* The ResNet-50 model used in this study requires substantial computational resources for both training and inference. This could pose a significant challenge in low-resource environments, such as small-scale farms, where access to high-performance computing systems is limited. To address this issue, future studies should explore more computationally efficient models or optimizations, such as quantization or pruning, that retain model performance while reducing resource consumption.
5. *Imbalanced Data Distribution:* The dataset exhibited some imbalance in the number of training images across the various sugarcane growth stages, which could have introduced biases during model training. Specifically, underrepresented growth stages may have led to the model underperforming in detecting these stages when applied to new data. Data augmentation techniques, or the collection of additional images from underrepresented stages, could help mitigate this problem in future work.

6. *Temporal Coverage Limitations:* The dataset used in this study covered only specific growth stages of sugarcane (2, 4, 6, 9, and 11 months), excluding intermediate stages and complete growth cycles. This limited the model's ability to learn the entire sugarcane growth process and understand how environmental factors like seasonal changes, pests, and fertilization schedules might affect crop development throughout the year.

Further Research

1. *Expand Dataset Collection:* Future studies should expand the geographical and environmental scope of the study by incorporating data from different sugarcane-growing regions, varying soil types, and diverse climatic zones. This improves the model's adaptability and generalizability, allowing for a broader application of the findings.
2. *Integrate Multispectral and Thermal Imaging:* To improve the classification accuracy, future research should integrate multispectral and thermal imaging with RGB imagery. Multispectral images can provide deeper insights into crop health and stress conditions, whereas thermal imaging can help assess moisture levels and detect early signs of disease, thus complementing data collected from visible light cameras.
3. *Optimize Models for Deployment:* There is a need for further research into lightweight and efficient architectures, such as MobileNet and EfficientNet, to make real-time applications more feasible in low-resource agricultural settings. Optimizing models for edge devices could ensure that AI-based crop monitoring systems can be deployed in a broader range of environments.
4. *Diversify Data Collection Conditions:* Capturing images under different lighting conditions, weather patterns, and at various times of the day can improve the model's robustness to real-world challenges. By considering diverse weather conditions such as cloud cover, varying sunlight, and even overcast skies, the model can be better equipped for real-world deployment.
5. *Include Intermediate Growth Stages:* Collecting additional data on intermediate growth stages will provide a more detailed and nuanced understanding of the sugarcane lifecycle, which could improve the model's predictive capabilities across all stages of growth.
6. *Conduct Longitudinal Studies:* Future research should include longitudinal studies that span the entire sugarcane growth cycle. By tracking environmental factors such as rainfall, pest infestations, and nutrient availability over time, it is possible to assess how these factors influence growth patterns and model performance.
7. *Field-Based Validation: C*onducting field-based validation in real agricultural environments will allow researchers to assess the model's practical performance and identify any limitations in its operational use. Field trials can provide invaluable feedback for adjusting model parameters or addressing specific challenges faced by farmers in the real world.
8. *Adopt Explainable AI Techniques:* Employing explainable AI methods, such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations), could improve the transparency of a model's predictions. This would enhance its trustworthiness among farmers and agronomists, who would be better able to understand why certain predictions were made and how they could be applied to improve farm management.
9. *Develop Integrated Precision Agriculture Systems:* Future research could focus on developing systems that integrate the model's predictions into broader decision-making tools. These systems can assist with irrigation, fertilization, pest control, and harvest planning, enabling farmers to make more informed decisions and optimize resource use.

10. *Collaborate with Experts and Policymakers:* Collaboration with agricultural research institutions, policymakers, and industry stakeholders is essential for standardizing methodologies and ensuring the large-scale adoption of AI-based crop monitoring systems. Such collaborations could facilitate the development of policies supporting precision agriculture and provide guidelines for its implementation on a national scale.

In summary, while this study provides valuable insights into the application of AI in crop monitoring, several areas remain unexplored or underexplored. By addressing the limitations outlined above, future research can make significant strides toward improving the accuracy, applicability, and deployment of AI-driven solutions for sugarcane growth monitoring and other agricultural applications.

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