

Vision-Based Classification Of Red Chilli (Capsicum Annuum L.) Varieties Using Pre-Trained Neural Networks

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Abstract

Background: Chili is one of the most commercially important spice crops in India, playing a vital role in agriculture-based livelihoods, food processing industries, and export markets. Popular varieties such as Byadagi and Guntur are highly valued for their distinct color, pungency, and quality attributes. With increasing demand for quality assurance and automation in post-harvest processing, there is a growing need for intelligent systems capable of accurately classifying chili varieties based on visual characteristics. Advances in deep learning and computer vision offer promising solutions to address these challenges and enhance efficiency in smart agriculture applications.

Methods: A deep learning-based automated chili classification framework was developed using transfer learning with pre-trained AlexNet and GoogLeNet architectures. The system exploits visual features such as color, texture, shape, and surface patterns to distinguish between Byadagi and Guntur chili varieties. The entire framework was implemented in MATLAB AlexNet and GoogLeNet pre trained deep neural network modules, enabling systematic dataset preprocessing, training, validation, and performance visualization. The models were evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis.

Result: Experimental results demonstrate that both deep learning models achieved high classification performance, indicating strong generalization capability. AlexNet attained a classification accuracy of 100%, while GoogLeNet achieved 99.68% accuracy. Overall, the proposed approach proves to be a robust and scalable solution for automated chili classification, with significant potential for deployment in mobile-based recognition systems and conveyor-based grading and packaging units in smart agriculture.

Key words: GoogLeNet, AlexNet, Byadagi, Guntur.

Introduction

Accurate and efficient identification of crop varieties is fundamental to many post-harvest operations in the agri-food supply chain, including sorting, grading, packaging, traceability and quality control. For high-value spices such as Chili (*Capsicum annum* L.), morphological and visual attributes-color, length, surface texture and shape-are routinely used by human graders to distinguish commercially important cultivars such as Byadagi and Guntur. However, manual inspection is time-consuming, subjective, and error-prone, which motivates automated computer-vision solutions that deliver consistent, scalable, and low-latency classification at packing houses and on processing conveyors. Recent advances in convolutional neural networks (CNNs) and transfer learning have made it possible to capture subtle visual differences across cultivars and maturity stages, enabling real-time deployment in mobile apps and embedded grading systems. This study builds on that momentum and evaluates transfer-learning

using AlexNet and GoogLeNet within the MATLAB environment for classifying two widely grown Chili varieties: Byadagi and Guntur.

Recent literature on computer vision in agriculture demonstrates a clear transition from handcrafted descriptors to end-to-end deep learning pipelines. Several studies highlight growing adoption of CNNs and vision-based systems for chili sorting, defect detection, and automated grading, emphasizing their practical relevance to the processing industry. These studies collectively illustrate how deep learning strengthens the agricultural value chain by ensuring consistent quality inspection and reducing human subjectivity, trends also noted in recent reviews of smart agricultural imaging systems (Hossen et al. 2025).

Transfer learning-which fine-tunes models pretrained on large-scale datasets such as ImageNet-has emerged as a dominant strategy in agricultural computer vision, especially where domain-specific datasets are limited. A detailed review by Hossen et al. confirms that transfer learning significantly improves classification accuracy and reduces model development time in crop-related tasks, outperforming conventional handcrafted methods in robustness and feature representation (Hossen et al. 2025). These findings provide strong justification for the use of AlexNet and GoogLeNet in the present work, as both networks offer reliable pretrained feature hierarchies that adapt effectively to small- and medium-sized agricultural datasets.

Comparative studies evaluating pretrained CNNs for plant species and crop-quality recognition further show that network architecture plays a crucial role in performance. Research comparing AlexNet, GoogLeNet, VGG, and ResNet architectures indicates that although deeper networks often achieve slightly higher accuracy, classic architectures like AlexNet and GoogLeNet remain competitive, especially in applications with limited training data or computational constraints (Deep Learning Toolbox - MATLAB n.d.). These works also highlight that performance differences often arise from input-resolution compatibility, receptive field size, and depth-related feature extraction behavior-observations directly relevant to our experimental results.

There is also growing evidence that MATLAB's deep learning toolbox serves as a reliable environment for agricultural image analysis. Several applied studies in fruit, disease, and crop classification have successfully implemented full workflows in MATLAB, demonstrating its ease of dataset handling, augmentation, and model tuning (Naik, Malmathanraj, and Palanisamy 2022). These studies confirm that reproducibility and rapid experimentation are essential advantages for domain researchers, particularly those working with institution-scale datasets. In addition, papers focused on Chili variety classification using CNNs validate the feasibility of distinguishing cultivars based on morphology and surface patterns, further supporting the approach adopted in this study (Fu, Guo, and Huang n.d.).

Despite the promising progress, three gaps are evident in existing literature. First, most studies focus on disease detection or maturity estimation rather than cultivar-level discrimination between visually similar Chili varieties. Second, end-to-end MATLAB-based frameworks dedicated to industrial deployment-covering data acquisition, transfer learning, evaluation and reproducibility-are limited. Third, the influence of architectural differences such as depth, receptive-field configuration, and inception-module design on small inter-class visual variations

remains underexplored. The present study addresses these gaps by (a) constructing a curated Chili-variety dataset, (b) implementing reproducible transfer-learning pipelines using AlexNet and GoogLeNet, and (c) evaluating performance through accuracy, precision, recall, F1-score, and confusion-matrix-based analysis.

The contributions of this work are twofold. Practically, it demonstrates a deployable computer-vision pipeline capable of supporting mobile-based recognition tools and conveyor-integrated grading systems, reducing manual errors and accelerating post-harvest workflow. Scientifically, it provides an empirical comparison linking architectural properties to classification outcomes for chili varieties, offering insights for researchers developing lightweight or industrially optimized models. Given that recent literature emphasizes the urgent need for reproducible studies bridging academic research and real industrial deployment, especially for high-value spices where precision grading is economically significant, this study contributes timely empirical evidence.

The study (Bezabh et al. 2023) supports the feasibility of deploying deep learning-based pepper recognition systems on edge devices. introduced CPD-CCNN, a concatenated deep learning framework for pepper disease classification that integrates multiple feature extraction layers. The model demonstrated improved robustness and classification accuracy across diverse disease classes. This research highlights the importance of architectural design in capturing subtle visual variations in pepper-related imagery. In (Yudantoro et al. 2025) evaluated the performance of multiple deep learning models for classifying dried chili varieties using digital image analysis. Their findings revealed that CNN-based approaches outperform conventional machine learning techniques in distinguishing visually similar chili samples, reinforcing the relevance of deep learning for post-harvest chili classification. The study reported in (Hendrawan et al. 2021) explored deep learning techniques for classifying large green chili maturity stages. Using image-based CNN models, the authors demonstrated accurate maturity classification, indicating that visual cues such as color and shape can be effectively learned by deep networks. This work further supports CNN applicability for chili quality assessment.

The LGENetB4CA, a novel deep learning architecture tailored for chili classification tasks (Van et al. 2025). The model achieved high accuracy by effectively combining depth and feature reuse strategies. Their research underscores the role of customized CNN architectures in improving crop-specific classification performance. The investigated intelligent recognition systems for automated chili production using deep learning by (Tai et al. 2025) integrated CNN-based recognition with production automation, highlighting the industrial relevance of deep learning models in chili grading and processing pipelines.

The Ide-Cabe framework presented in (Suwarningsih et al. 2022) focused on chili variety identification using leaf images and deep learning techniques. The authors demonstrated that CNNs can successfully differentiate chili cultivars based on morphological patterns, supporting the feasibility of variety-level classification using visual data. An applied transfer learning for durian variety classification in (Voo Nyuk Mee, Lim Tong Ming, and Lim Yee Mei, Mar), presenting a methodology closely related to cultivar-level agricultural classification. Their results showed

that pretrained CNNs can generalize effectively across fruit varieties, providing methodological insights transferable to chili variety classification.

The work in (Bohari et al. 2025) presented a real-time crop sorting system using ESP32-CAM and YOLO-based object detection. The system demonstrated efficient on-line sorting, highlighting the potential of deep learning models in automated agricultural grading systems. Abubeker et al. [13] proposed a computer vision-assisted real-time chili classification and sorting framework using a bird's-eye camera setup. The study validated the integration of CNN models into practical sorting environments, aligning closely with automated chili grading objectives.

The study on development of an automated conveyor-based sorting and grading system for red chili peppers using image processing and artificial neural networks proposed in (Lestari, Kurniawan, and Wahab 2024). Their results demonstrated improved consistency and reduced manual intervention, emphasizing the importance of automation in post-harvest processing. A study in (Mohi-Alden et al. 2023) introduced a machine vision-based intelligent model for in-line bell pepper sorting. Although focused on bell peppers, the study demonstrated how CNN-based systems can be effectively deployed in industrial agricultural settings, offering insights applicable to chili grading systems.

A smartphone-based application using a modified in (Babatunde et al. 2024) VGG16 architecture for early plant issue detection. The study demonstrated the effectiveness of mobile-friendly deep learning models, supporting the development of chili recognition applications for farmers and supply chains. The Ayush Net framework presented in (N and A 2024) proposed an IoT-based mobile application for automatic plant classification using deep learning. The integration of cloud and edge intelligence in this work highlights future directions for scalable agricultural recognition systems. The mobile plant recognition system discussed in (Gao, Lin, and Sinnott 2017) explored deep learning-based classification on handheld devices. The study reinforced the growing trend of deploying CNN-based agricultural recognition tools in mobile environments, relevant to chili variety identification applications.

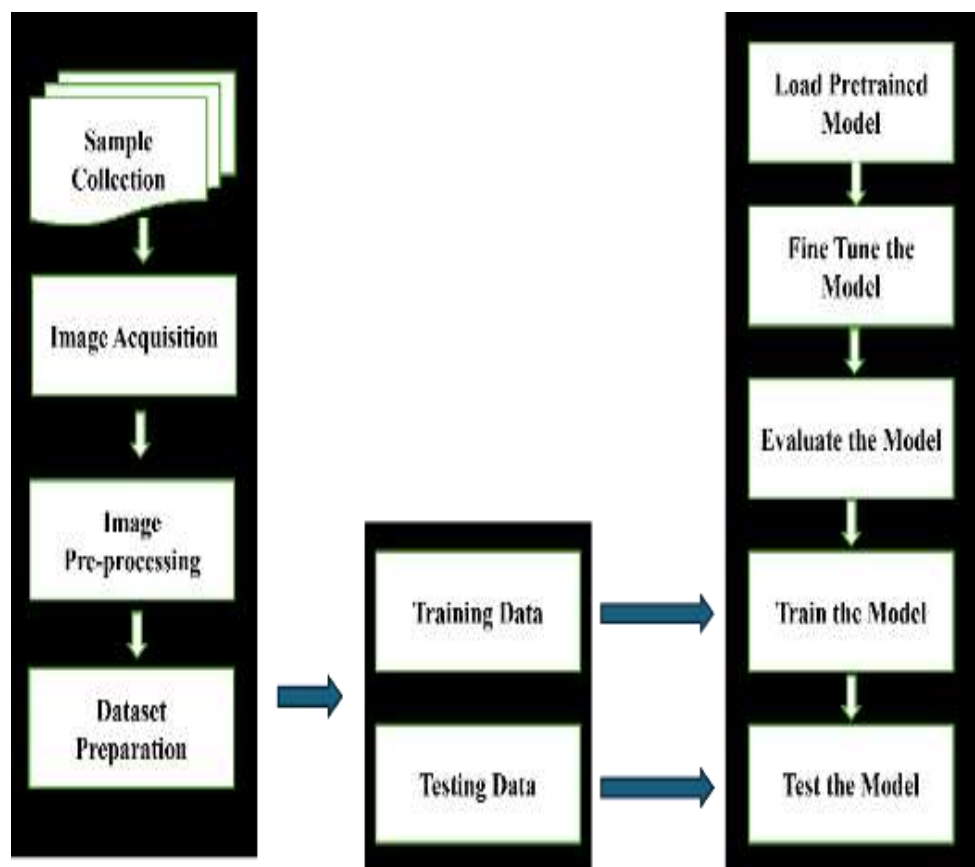
A study in (Mohammadi et al. n.d.) explored spectral discrimination of crops and weeds using deep learning combined with wavelet transforms. Their work demonstrated that deep models can capture complex feature representations, suggesting potential extensions of visual chili classification to multispectral domains. In (Sambana et al. 2025) investigated transfer learning using YOLO variants for efficient plant disease detection. Their findings emphasized the importance of model selection and fine-tuning strategies for achieving real-time performance in agricultural applications. The survey presented in (Wang et al. 2025) reviewed recent advances in deep learning for plant disease detection, highlighting trends, challenges, and future research directions. This work contextualizes the growing adoption of CNNs in agricultural image analysis. A transfer learning techniques are applied in (Zhang et al. 2025) for improved crop yield prediction. Although yield-focused, their work demonstrated the versatility of pretrained models in agricultural analytics, reinforcing the broader applicability of transfer learning frameworks. The hyperspectral image-based discrimination are explored in (Kaushik, Nidamanuri, and Aparna 2025) for vegetable crops using deep learning. Their results demonstrated enhanced

classification accuracy, indicating future research possibilities for integrating spectral features into chili classification systems. An Agarwood Net, a lightweight deep learning architecture proposed by (Shafik et al. 2025) for multi-plant biotic stress classification. The study emphasized efficiency and generalization, aligning with the need for scalable agricultural recognition models. Finally, the survey in (Zidi et al. 2025) reviewed machine learning and deep learning techniques for crop mapping and precision agriculture. The authors highlighted the role of automated visual analysis in improving agricultural productivity, reinforcing the significance of deep learning-based chili classification systems within smart agriculture ecosystems.

Material And Methods

This study proposes a deep learning-based approach for the classification of Byadagi and Guntur red chili varieties through transfer learning using pretrained convolutional neural networks (CNNs). The methodology comprises major stages like sample collection, dataset preparation, preprocessing and model development as shown in Fig 1. Each stage was designed to ensure high-quality input images suitable for training deep neural architectures while maintaining consistency, reproducibility, and robustness of the classification pipeline.

Figure 1: Methodology



The process began with dataset creation; wherein fresh Chili samples were manually collected from farms and local markets across the respective geographical regions. A total of 600 images were acquired, ensuring an equal representation of 300 samples for each Chili class. The samples of Byadagi and Guntur Red Chili images are as shown in Figure 2.

All images were captured under controlled laboratory conditions using a digital camera with advanced optical specifications, maintaining a uniform background and constant illumination to avoid shadows, glare, or color distortions. After acquisition, the images underwent a structured preprocessing pipeline to ensure dataset uniformity and robustness. Each image was cropped to remove unnecessary background regions and resized to a fixed dimension suitable for convolutional neural network (CNN) architectures. Further, contrast enhancement and brightness adjustment techniques were applied to normalize lighting variations, while maintaining the natural texture and color of the Chili samples. The prepared dataset was then split into training, validation, and testing subsets, ensuring that the model was evaluated on unseen images for unbiased performance assessment.

Figure 2: Guntur Chili (Left side) and Byadagi Chili (Right side) samples



All images were captured under controlled laboratory conditions using a digital camera with advanced optical specifications, maintaining a uniform background and constant illumination to avoid shadows, glare, or color distortions. After acquisition, the images underwent a structured preprocessing pipeline to ensure dataset uniformity and robustness. Each image was cropped to remove unnecessary background regions and resized to a fixed dimension suitable for

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Following dataset preparation, the images were fed into multiple pretrained convolutional neural networks using transfer learning. Models such as AlexNet, GoogLeNet, were selected due to their proven effectiveness in agricultural image classification tasks. The final layers of these pretrained models were replaced with customized fully connected layers suitable for binary classification. Data augmentation strategies, including random rotations, flips, and zoom operations, were embedded in the training phase to improve model generalization. The training process was conducted using stochastic gradient descent-based optimization, with hyperparameters fine-tuned iteratively to achieve optimal convergence. Accuracy, precision, recall, and F1-score were used as performance metrics to evaluate the classification efficiency of each model. The overall workflow of the study—from image acquisition and preprocessing to model training, validation, and final prediction—is represented in the block Figure 1, highlighting the sequential steps involved in the complete system pipeline. This integrated methodology ensures the development of a reliable Chili-classification framework capable of supporting automated grading, quality monitoring, and market-level standardization applications.

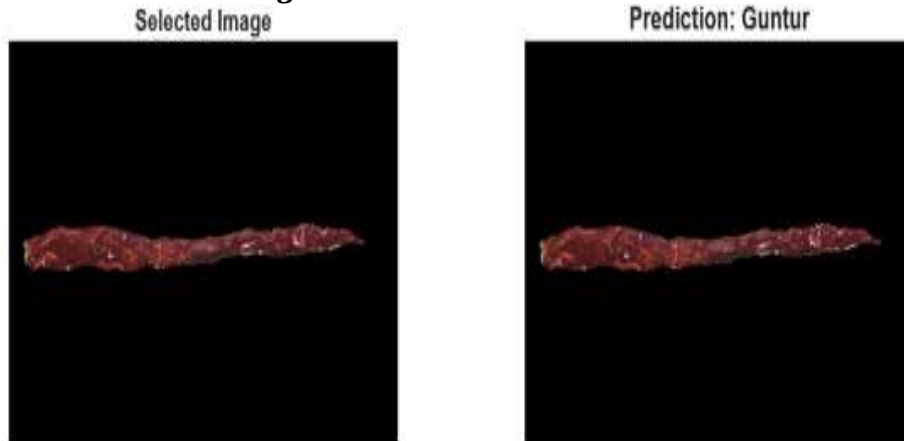
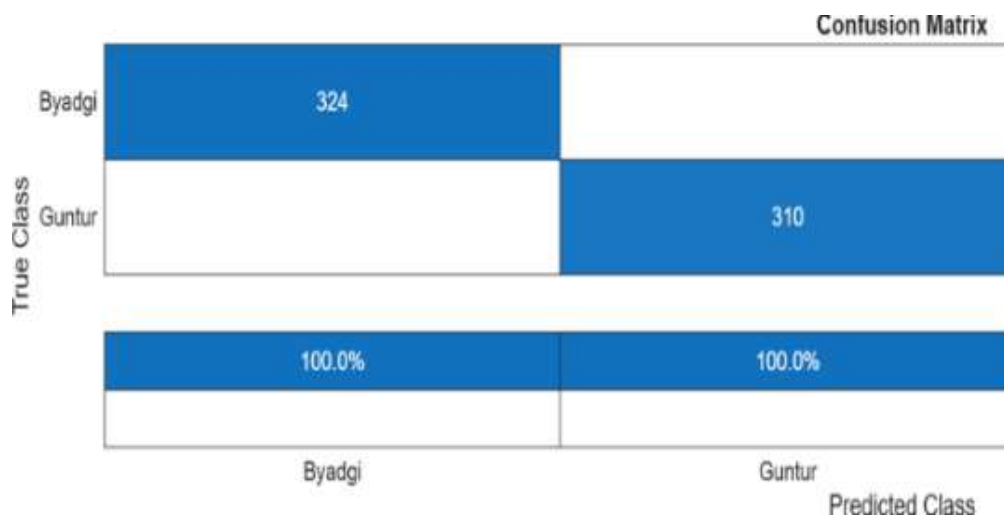
Results And Discussions

Using an Intel processor with 12th Gen Intel(R) Core (TM) i3-1215U (1.20 GHz) with 8GB of RAM and Windows 11 Home Single Language, the complete work was implemented using MATLAB is R2025b, launched around September 2025. AlexNet uses a total of 25 layers, out of which 8 are main learnable layers that include 5 convolution layers and 3 fully connected layers. These layers help the model extract important features from Chili images and classify them accurately. GoogLeNet is a deep CNN with 144 layers, including 22 learnable layers arranged inside 9 Inception modules. These layers allow the model to learn features at multiple scales, making it more powerful for complex image classification tasks. The experimental results show that both AlexNet and GoogLeNet, trained using transfer learning, classify Byadagi and Guntur chilies with very high accuracy. AlexNet achieved 100% accuracy, while GoogLeNet achieved 99.68%, as shown by the confusion matrices. AlexNet performed slightly better because its simpler and shallower architecture works well with small datasets and two-class problems.

Table 1: Parameters of the Models

Network Parameters	Pretrained Neural Network Models	
	AlexNet	GoogLeNet
Depth	8	22
Batch Size	16	16

Network Parameters	Pretrained Neural Network Models	
	AlexNet	GoogLeNet
Validation Accuracy	100	99.68
Learning Rate	0.0001	0.0001
Epoch	5	5
Image Input Size	227 by 227	224 by 224

Figure 3a: AlexNet validation**Figure 3b: AlexNet Confusion Matrix**

The Figure 3 and 4 illustrates the validation performance of the AlexNet and GoogLeNet based Chili variety classification model. The Figure 3a and 4a shows a representative test image selected from the validation dataset and the corresponding model prediction, where the network correctly identifies the sample as the Guntur and Byadagi Chili variety, demonstrating effective feature learning from visual cues such as shape, texture, and color. The Figure 3b and 4b presents the confusion matrix obtained during validation, which summarizes the classification outcomes for both classes, Byadagi and Guntur.

Figure 4a: GoogLeNet validation

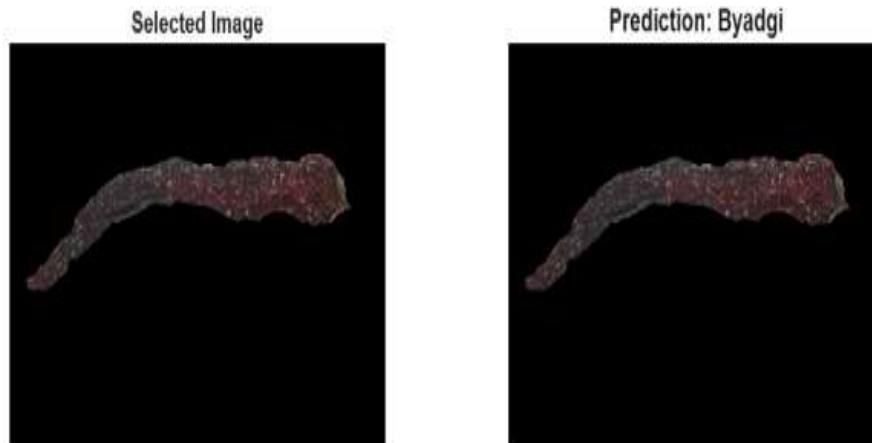


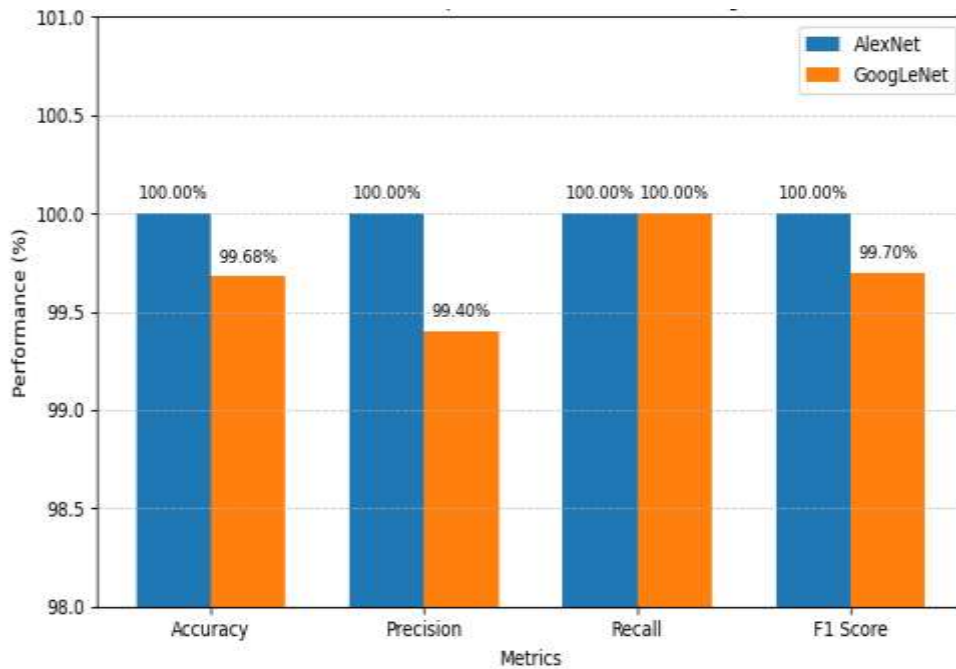
Figure 4b: GoogLeNet Confusion Matrix

		Confusion Matrix	
True Class	Byadgi	324	
	Guntur	2	308
		Byadgi	Guntur
		99.4%	100.0%
		0.6%	
		Predicted Class	

GoogLeNet, although deeper and more complex with its inception modules, showed slightly lower accuracy due to multi-scale feature extraction, which can sometimes cause confusion when the dataset is small or when classes look visually similar. The few misclassifications in the Guntur class were likely due to variations in lighting, texture, and orientation. Increasing dataset size or using more augmentation can help improve GoogLeNet's generalization.

Although GoogLeNet has strong feature extraction abilities, it requires more computational power. AlexNet, despite having more parameters, trains faster and performs more reliably on small datasets and mid-range systems. Overall, both models outperform classical methods, but AlexNet gives perfect classification, making it highly suitable for real-time Chili grading and sorting applications.

Figure 5: Models Accuracy



Conclusion

In this study, AlexNet and GoogLeNet were successfully used to classify Byadagi and Guntur red chilies using deep learning. The results showed in Figure 4 that AlexNet achieved 100% accuracy, while GoogLeNet achieved 99.68%, other performance parameters like precision, recall and F1 score proving that both models are highly effective for Chili classification. AlexNet worked slightly better because its simpler architecture fits well with a small dataset and a two-class problem, while GoogLeNet's deeper design gives powerful feature extraction but needs more data for perfect accuracy.

Overall, the study shows that deep learning performs much better than traditional machine learning methods and can reliably classify Chili varieties. This system can be improved further by collecting more images, adding real-time image capture and deploying the model on mobile or IoT-based sorting machines for use in the agriculture industry.

Acknowledgment

The authors sincerely thank the Management and Department of Electronics and Communication Engineering of Ballari Institute of Technology and Management, Ballari. The authors also acknowledge the assistance of students and colleagues involved in data collection and image acquisition. Special thanks to Krishi Vidya Kendra-Hagari, Ballari District, Karnataka.

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