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Thermal Image-Based Classification of Okra Maturity: A Comparative Study of CNN, SVM, and LSTM

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Abstract: Post-harvest quality assessment remains a major challenge in agriculture, particularly for okra (Abelmoschus esculentus), which deteriorates rapidly due to high moisture content. Traditional grading based on manual inspection often results in inconsistency and product damage. This study explores thermal imaging as a non-destructive alternative for okra maturity classification. A dataset of 501 thermal images was acquired under controlled conditions and analyzed using three machine learning models: Convolutional Neural Network (CNN), Support Vector Machine (SVM) with Histogram of Oriented Gradients (HOG) features, and Long Short-Term Memory (LSTM) network. Experimental results show that CNN achieved the highest accuracy (99.01%), outperforming SVM (95.05%) and LSTM (91.09%). Confusion matrix and ROC analyses confirmed CNN's superiority in capturing spatial thermal patterns related to maturity stages. Compared with RGB or hyperspectral imaging reported in prior studies, thermal imaging integrated with AI provides a more robust, illumination-independent, and non-destructive solution. The findings demonstrate the potential of CNN-based thermal imaging systems for automated sorting of okra in agricultural supply chains. Future work will focus on larger datasets, multi-class maturity levels, and real-time implementation to enhance practical deployment in post-harvest management.

Keywords: CNN; LSTM; Okra maturity; SVM; Thermal imaging

Introduction

The agricultural sector continues to face significant challenges in improving efficiency and minimizing post-harvest losses, which may reach up to 30–40% of total production (FAO, 2020). Okra (Abelmoschus esculentus), a widely cultivated vegetable, is particularly vulnerable to rapid deterioration after harvest due to its high moisture content and delicate texture. Beyond its agricultural importance, okra also possesses notable health benefits. Mokgalaboni et al. (2023) reported that okra supplementation significantly improves glycaemic control in pre-diabetic and type 2 diabetic patients, highlighting its potential as a functional food. This underlines the necessity of maintaining its post-harvest quality to preserve its nutritional and therapeutic value. Ensuring accurate grading of okra (*Abelmoschus esculentus*) based on maturity is critical for maintaining quality, extending shelf life, and securing market value.

Traditionally, maturity assessment has relied on manual inspection, which is often inconsistent, time-consuming, and may cause physical damage to the product. Consequently, non-destructive approaches using imaging technologies have gained growing attention as reliable alternatives. Imaging technologies have been increasingly adopted for analyzing natural objects and agricultural products, ranging from

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environmental mapping using satellite imagery (Nurhasanah et al., 2023) to ripeness detection using visible and thermal sensors. These applications highlight the versatility of imaging approaches in supporting automated inspection systems. Previous studies have applied RGB and hyperspectral imaging to evaluate ripeness, reporting promising results (Abd-Elhameed et al., 2022; Fekadu Gemede, 2015). Similarly, Raikar et al. (2020) employed deep learning models such as AlexNet, GoogLeNet, and ResNet50 for classifying okra grades based on pod length and physical characteristics, achieving up to 99% accuracy with the ResNet50 model. While their study relied on RGB imaging, the present work extends this concept by utilizing thermal imaging for a non-destructive and illumination-independent classification approach.However, these methods remain sensitive to lighting variations and often require complex imaging setups, limiting their applicability in real post-harvest environments.

Thermal imaging offers a novel, illumination-independent approach by capturing surface temperature distributions that reflect physiological processes such as respiration and transpiration (Gozali, 2023; Lin & Fan, 2004) . These thermal signatures can indicate maturity-related changes without external illumination (Zeng et al., 2020). Recent research has also demonstrated the effectiveness of thermal imaging combined with deep learning for fruit quality assessment. For instance, Lin et al. (2023) employed an improved YOLOv5s model using cold excitation thermal images to detect bruises on apples, showing that thermal-based object detection methods can accurately identify surface and subsurface defects in post-harvest produce. Despite this advantage, the application of thermal imaging for maturity classification remains largely underexplored, creating a research gap in developing practical, non-destructive, and automated grading systems for perishable crops. Addressing this gap is crucial to improving post-harvest management, reducing waste, and supporting sustainable agricultural practices.

Recent advances in artificial intelligence (AI), particularly in machine learning and deep learning, have greatly enhanced the ability to process and interpret complex imaging data (Hespeler et al., 2021; Koirala et al., 2019; Raju et al., 2023; Wilson et al., 2023; Zhou et al., 2019). In the agricultural sector, deep learning has also been widely utilized for predictive modeling. (Murugesan et al., 2022) demonstrated the effectiveness of various LSTM architectures, including CNN-LSTM hybrids, in forecasting agricultural commodity prices, emphasizing the adaptability of these models to complex temporal patterns—a capability similarly leveraged in the present study for analyzing thermal image sequences of okra maturity.

Convolutional Neural Network (CNN) have shown high effectiveness in visual pattern recognition and classification tasks (Breland et al., 2021; Gao et al., 2020; Sobayo et al., 2018). Meanwhile, other models such as Long Short-Term Memory (LSTM) network (Guo et al., 2023; M. Elshewey et al., 2023) and Support Vector Machine (SVM) (Caesarendra et al., 2019; Narayanan et al., 2021; Selvathi & Suganya, 2019), have also been applied in various non-sequential domains with varying levels of success.

In this study, we propose a comparative analysis of Convolutional Neural Network, Support Vector Machine with Histogram of Oriented Gradients (HOG) features, and Long Short-Term Memory network for classifying okra maturity using thermal imaging. The study aims to develop a thermal image-based classification model capable of identifying okra maturity stages, while also comparing the performance of CNN, SVM, and LSTM in terms of accuracy and robustness. Furthermore, it seeks to evaluate the feasibility of thermal imaging as a practical, non-destructive approach for post-harvest quality assessment. Unlike previous works that primarily employed RGB or hyperspectral images, this research emphasizes thermal data integrated with AI algorithms, thereby providing new insights into intelligent post-harvest management. (Alzubaidi et al., 2021).

Method

Dataset and Experimental Design

This study utilized the dataset reported by Sasithradevi et al. (2024), comprising 501 thermal images of okra obtained from local farms and vegetable vendors. The dataset is categorized into two classes: 253 images of overripe okra and 248 images of adequately ripe okra. All images, saved in .jpg format with radiometric properties, were captured using a FLIR E75 thermal camera with a native resolution of 320 × 240 pixels and an upscaled resolution of 640 × 480 pixels. Data acquisition was performed under controlled conditions to ensure consistency in temperature and imaging parameters, with average surface temperatures recorded at 34.23 °C (SD = 1.17) for overripe okra and 31.40 °C (SD = 1.01) for adequately ripe okra. Similar thermal datasets have also been reported by Pathmanaban et al. (2023), who collected okra thermal images under different storage conditions to analyze temperature variation and deterioration patterns. This supports the current study's approach of using thermal features for maturity assessment.

Representative thermal images of okra maturity are shown in Figure 1. These examples illustrate the temperature distribution differences between adequately ripe and overripe okra, where color variations correspond to thermal intensity levels. The images provide a clear visual indication of how ripeness influences the thermal profile of the produce, forming the basis for classification using machine learning models.

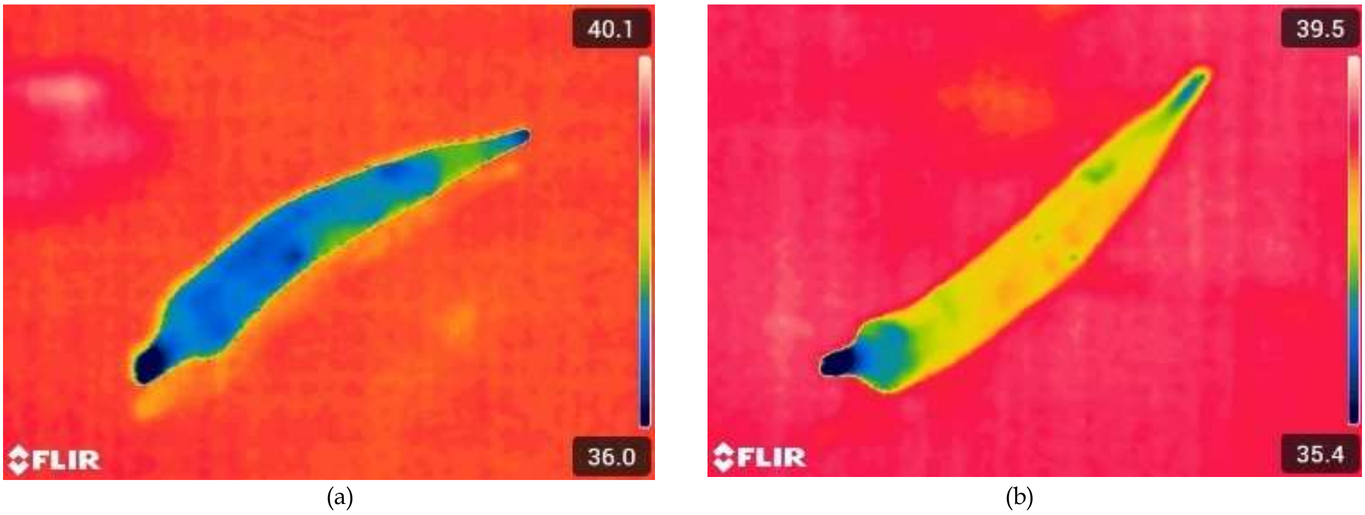

Figure 1. Representative thermal images of okra maturity: (a) adequately ripe and (b) overripe

Data Processing and Classification

The methodology of this study consisted of four main stages: dataset preparation, feature extraction, model training, and performance evaluation. Thermal images of okra were preprocessed and divided into training and testing sets to ensure unbiased evaluation. Three different classification approaches were implemented, namely CNN, SVM with (HOG) features, and LSTM. The overall workflow of this study is illustrated in Figure 2.

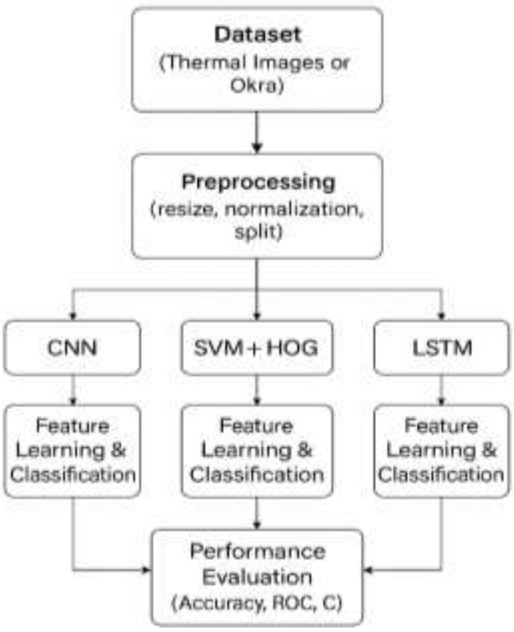

Figure 2. Workflow of the proposed methodology for data classification

CNN Approach

CNNs were applied to extract spatial patterns from the thermal images of okra. The structure and operation of the CNN model in this study were adapted from common deep learning architectures successfully implemented in other domains, such as text and image classification (Islami et al., 2024; Noor et al., 2023). Each convolutional layer applies a kernel filter to the input feature map, mathematically expressed as:

$$h^k = f(w^k * x + b^k) \quad (1)$$

Where bias b^k and weight w^k for generating k feature maps h^k with a size of *(m-n-1)* each and convolved with input (Alzubaidi et al., 2021).

SVM with HOG Features Approach

The Histogram of Oriented Gradient was employed for feature extraction prior to classification with the Support Vector Machine. This procedure involved several key stages, as described by Bai et al. (2022) and Huu et al. (2021). Similar to the texture- and color-based feature extraction approaches explored by Rizki et al. (2024), this study utilizes Histogram of Oriented Gradients (HOG) features to capture spatial texture information from thermal images prior to classification with SVM. First, Gamma correction was applied to reduce the influence of illumination variation ensuring uniform brightness across the thermal images, as expressed,

$$I(x, y) = I\,(x, y)^{\gamma} \quad (2)$$

Next, horizontal and vertical gradients were computed to capture edge information, defined as

$$G_x(x,y) = H(x+1,y) - H(x-1,y),$$
$$G_y(x,y) = H(x,y+1) - H(x,y-1) \quad (3)$$

The gradient magnitude and orientation at each pixel were then obtained using

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (4)$$
$$\alpha\,(x,y) = tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \quad (5)$$

Subsequently, gradient orientations were accumulated into histograms within localized cells and normalized over adjacent blocks to enhance robustness against illumination and contrast variations. Finally, all normalized histograms were concatenated into a single feature descriptor, which served as the input to the SVM classifier.

LSTM Approach

The LSTM network was employed to capture sequential dependencies by flattening thermal images into vector sequences. The gating mechanism regulates information flow, defined as:

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \quad (6)$$
$$\tilde{C}_t = \tan h\,(W_C.[h_{t-1}, x_t] + b_C) \quad (7)$$
$$C_t = f_t.C_{t-1} + i_t.\tilde{C}_t \quad (8)$$
$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (9)$$
$$h_t = o_t.\tan h\,(C_t) \quad (10)$$

Where f_t, i_t and o_t are the forget, input, and output gates, respectively; C_t represents the cell state, and h_t is the hidden state. This architecture enables the LSTM to learn temporal patterns in thermal signatures of okra maturity (Miśkiewicz & Witkowicz, 2025; Suhendra et al., 2025). The effectiveness of LSTM in modeling sequential dependencies has also been validated in other domains. Song et al., 2020 employed an LSTM neural network to predict time-series well performance in petroleum reservoirs, showing that the model can accurately capture complex temporal relationships—an essential characteristic also leveraged in the current study for analyzing sequential thermal image data.

Performance Evaluation

Classifier performance was evaluated using accuracy, precision, recall, and F1-score. These metrics provide a balanced view of model reliability, with accuracy representing overall correctness, precision reflecting the proportion of true positives among predicted positives, recall capturing the proportion of true positives identified, and F1-score offering a harmonic mean of precision and recall (Çorbacıoğlu & Aksel, 2023; Heydarian et al., 2022; Sathyanarayanan, 2024; Wu, 2022). In addition, confusion matrices were generated for each classifier to illustrate the distribution of correct and incorrect predictions across maturity categories. Receiver Operating Characteristic (ROC) curves were also plotted from the experimental testing dataset, and the area under the ROC curve (AUC) was calculated. A higher AUC indicates stronger discriminative power between adequately ripe and overripe okra. By combining these evaluation methods, the study ensured a transparent and robust comparison of CNN, SVM, and LSTM classifiers for thermal image-based okra maturity classification.

Result and Discussion

CNN Result

The CNN model classified 50 adequately ripe and 50 overripe okra correctly, with only one misclassification from the 101 testing images. This corresponds to an overall accuracy of 99.01%, with precision and recall above 98% in both categories. The single error likely came from a borderline maturity stage, where thermal features overlapped. Overall, CNN demonstrated near-perfect classification, highlighting its potential for reliable non-destructive grading.

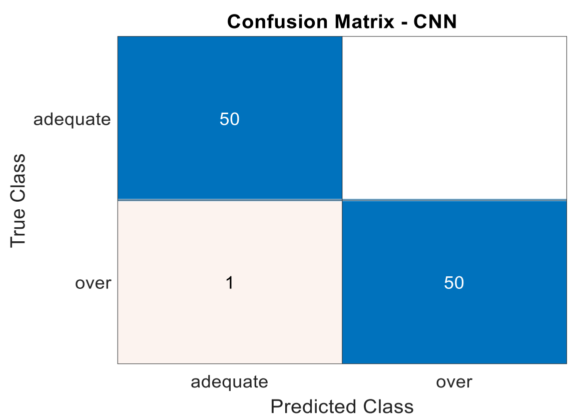

Figure 3. Confusion matrix of the CNN classifier on the testing dataset (n = 101). The model achieved an accuracy of 99.01% with only one misclassification, confirming its strong ability to extract spatial thermal features of okra maturity

SVM Result

The SVM with HOG features correctly classified 47 adequately ripe and 49 overripe okra, misclassifying three adequately ripe samples and two overripe samples. The resulting accuracy was 95.05%, with precision of 95.92% (adequately ripe) and 94.23% (overripe), and recall of 94.00% and 96.08% respectively. While less accurate than CNN, SVM provided balanced results with lower computational demands, making it suitable for scenarios where efficiency is prioritized.

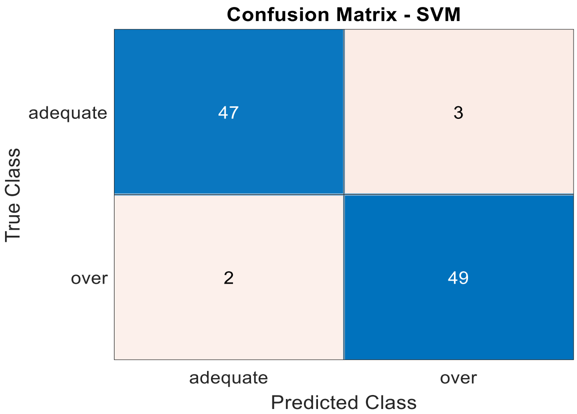

Figure 4. Confusion matrix of the SVM classifier with HOG features on the testing dataset (n = 101). The model reached an accuracy of 95.05%, with balanced precision and recall across both maturity classes

LSTM Result

The LSTM classifier correctly classified 47 adequately ripe and 45 overripe okra, with three and six misclassifications, respectively. This corresponds to an accuracy of 91.09%. Precision was 88.68% for adequately ripe and 93.75% for overripe, with recall of 94.00% and 88.24%. The relatively higher error rate in the overripe category reflects the limitations of LSTM for static images, since flattening image data into sequences reduces spatial information. Nonetheless, LSTM could be useful for time-series thermal data in future research.

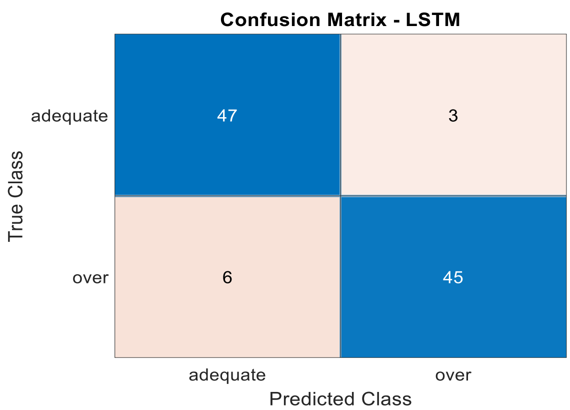

Figure 5. Confusion matrix of the LSTM classifier on the testing dataset (n = 101). The model produced an accuracy of 91.09%, with a higher misclassification rate in the overripe category, reflecting the limitations of LSTM for static thermal images

Comparative Evaluation

Table 1 and Figure 6 summarize the results of all three classifiers. CNN achieved the best accuracy (99.01%) and AUC (1.000), followed by SVM (95.05%, AUC 0.987) and LSTM (91.09%, AUC 0.979). CNN's strong performance reflects its ability to learn hierarchical features directly from thermal images. Similar trends were also reported by Sari et al. (2025), who demonstrated that Convolutional Neural Networks effectively classified mango ripeness levels based on digital imaging. This further supports the reliability of CNN architectures in identifying maturity-related patterns across different fruit types. SVM, although slightly less accurate, delivered robust results with lower computational needs. LSTM showed weaker performance due to its sequential design, but it may hold potential for future applications involving temporal thermal patterns. This observation aligns with findings from Malashin et al. (2024), who emphasized that LSTM networks are particularly effective when applied to time-dependent or sequential datasets, suggesting their potential for modeling temporal changes in agricultural thermal imagery.

Combining ROC and confusion matrix analyses provides a more comprehensive evaluation of classifier performance. While CNN is the most accurate option, SVM offers efficiency, and LSTM may be applicable to dynamic thermal data. Similar to the present findings, (Rahmahwati & Kirana, 2023) applied machine learning algorithms such as C4.5 and K-Nearest Neighbor to predict palm oil fruit production and demonstrated that data-driven approaches can significantly enhance decision-making in agricultural contexts. These results collectively highlight the potential of AI-based models to optimize crop management and quality control across various agricultural sectors.

Table 1. Comparison of classification accuracy and AUC.

Classifier	Accuracy (%)	ROC (AUC)
CNN	99.01	1.000
SVM	95.05	0.987
LSTM	91.09	0.979

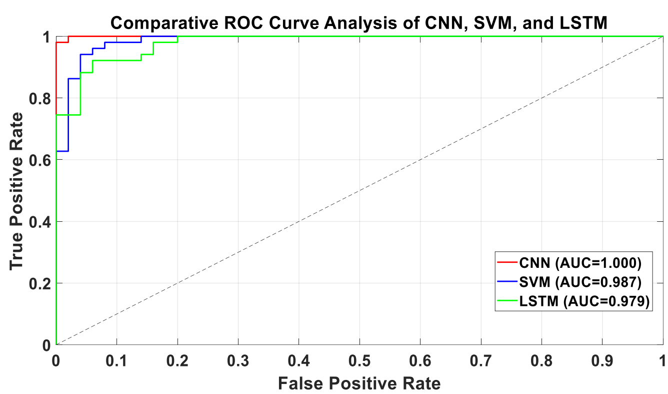

Figure 6. ROC curves of CNN, SVM, and LSTM classifiers on the testing dataset. CNN achieved the highest discriminative ability (AUC = 1.000), followed by SVM (AUC = 0.987) and LSTM (AUC = 0.979)

Conclusion

This study presented a comparative evaluation of CNN, SVM with HOG features, and LSTM networks for classifying okra maturity based on thermal imaging. Among the three approaches, CNN achieved the best performance with 99.01% accuracy and an AUC of 1.000, confirming its strong capability to capture subtle spatial thermal patterns associated with okra maturity. SVM achieved 95.05% accuracy with lower computational complexity, while LSTM reached 91.09% due to its limited ability to preserve spatial information when processing sequential image data. These results demonstrate that thermal imaging integrated with advanced machine learning models provides a robust, illumination-independent, and non-destructive alternative for post-harvest inspection. Beyond okra, the proposed framework can be generalized to other perishable crops requiring objective and rapid maturity evaluation. Its ability to operate independently of lighting conditions makes it suitable for practical applications in automated grading and sorting systems. The integration of CNN-based thermal imaging into agricultural supply chains could reduce human subjectivity, minimize post-harvest losses, and enhance the consistency of quality control. Despite its promising outcomes, this study is limited by the relatively small dataset, restricted maturity classes, and controlled laboratory environment. Future research should focus on expanding the dataset, incorporating multi-class grading, and implementing real-time analysis on mobile or embedded systems to strengthen applicability in real agricultural scenarios. Overall, this work contributes to the advancement of intelligent post-harvest management and supports the broader vision of data-driven smart agriculture.

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Author Contributions
Conceptualization, T. S.; methodology, I. R.; software, R. P.; data curation, I. R.; writing—original draft preparation, M. A. S.; funding acquisition, T. S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest.

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