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Performance Analysis of LVQ and Euclidean Distance for Chili Type Detection: The Impact of Training Iterations on System Generalization

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ABSTRACT

This research is driven by the challenges faced by farmers and consumers in Kerik Village, Magetan Regency, in accurately differentiating chili varieties, which impacts service quality and increases the risk of transactional errors. The study aims to implement and evaluate the effectiveness of an automated chili detection system by integrating the Learning Vector Quantization (LVQ) algorithm with the Euclidean Distance metric. The research methodology follows a structured flow, including the collection of primary digital images from local agricultural sites, grayscale pre-processing, and performance evaluation based on varying training iterations. The experimental results indicate that training intensity significantly influences the model's reliability. The system achieved its peak performance at 1,000 iterations, yielding a training accuracy of 71.67% and a superior testing accuracy of 85.00%. These findings demonstrate that the model possesses strong generalization capabilities without experiencing overfitting, outperforming several baseline agricultural classification studies. Practically, this automated tool provides a strategic solution for the farming community to mitigate misidentification risks, thereby enhancing product consistency and supporting localized smart farming initiatives.

1. Introduction

The era of the Industrial Revolution 4.0 has catalyzed a paradigm shift where Information Technology (IT) fundamentally dominates human activities [1]. This transition from manual processes to automated computerization necessitates accelerated research in IT to keep pace with global technological advancements.

A significant manifestation of this change is the shift in pattern recognition and classification [2]; tasks that previously required human expertise and a period of prolonged learning can now be executed efficiently through automated computer systems. In the agricultural sector, specifically in Indonesia, chili peppers represent a commodity with significant varietal diversity, including red chili, bird's eye chili, and curly chili. Distinguishing these varieties is crucial, particularly for stakeholders in the food processing industry, such as chili paste (sambal) producers, as each variety possesses distinct pungency levels and flavor profiles[3].

In regions like Kerik Village, Magetan Regency, the ability to accurately identify chili types is essential for farmers to ensure service quality and prevent transactional errors, especially when consumers lack the technical knowledge to differentiate between varieties.

To address the challenges faced by farmers and consumers in Kerik Village, the implementation of computer automation offers a strategic solution. This study proposes an automated detection system utilizing artificial neural networks, specifically the Learning Vector Quantization (LVQ) algorithm. LVQ has demonstrated robust performance in identification, diagnosis, and detection across various domains. In this research, LVQ is integrated with Euclidean Distance to develop a classification model based on digital imagery of chili varieties sourced directly from Kerik Village. The primary objective of this study is to implement and evaluate the effectiveness of the LVQ and Euclidean Distance methods in detecting chili varieties using localized datasets. By addressing how these methods can be effectively integrated into an automated system, this research aims to provide a reliable tool for the community to mitigate the risk of misidentification.

The scope of this investigation is focused on the application of the LVQ method for classifying chili types according to predefined target classes, while the Euclidean Distance metric is utilized during the system's recognition and feature-matching phase. The dataset employed in this study consists of digital images of chili peppers acquired directly from agricultural sites in Kerik Village, Magetan. Furthermore, the system's performance is rigorously evaluated using accuracy metrics to determine the model's effectiveness in resolving the classification problem.

The development of this detection system provides several key contributions to both the community and the field of information technology. Scientifically, it advances the application of specialized IT solutions within the agricultural domain, particularly in localized smart farming contexts. Practically, the system facilitates the accurate differentiation of chili varieties for daily consumption and industrial use, while simultaneously assisting farmers in the post-harvest sorting process to ensure product consistency and customer satisfaction. Ultimately, this research bridges the gap between sophisticated machine learning algorithms and practical agricultural challenges in rural Indonesia.

Explain the research context, gap, urgency, and contribution. The introduction should end with a concise statement of the study objective or hypothesis. Keep the narrative focused and grounded in recent literature from computing, information systems, or related interdisciplinary domains.

2. Literature Review

2.1 State-of-the-Art in Agricultural Classification

The integration of Artificial Intelligence (AI) in the agricultural sector has evolved significantly, particularly through the application of supervised learning for crop identification. A prominent algorithm in this domain is Learning Vector Quantization (LVQ), a competitive functional neural network. Previous research by Azhari and Supratman (2021) demonstrated the efficacy of LVQ in classifying pineapple varieties [4]. Their study utilized a dataset of 120 digital images, achieving a training accuracy of 88.88% and a testing accuracy of 83.33%. This high-performance underscores LVQ's ability to handle high-dimensional image data when paired with appropriate feature extraction.

However, the performance of LVQ is not uniform across all agricultural commodities. For instance, Utomo (2016) reported lower accuracy levels (50–53%) when applying LVQ to rice variety classification. Similarly, research on rice maturity detection based on leaf color by Utomo and Cahyono (2014) yielded testing accuracies of approximately 55%. These discrepancies suggest a critical research gap: the sensitivity of LVQ to the quality of input features and the complexity of the target classes. In more complex biological patterns, such as Frangipani (Kamboja) leaf identification, Gustina et al. (2016) highlighted that LVQ requires precise pattern recognition to differentiate between subtle morphological variations [5].

Recent trends have moved toward hybridizing LVQ with other image-processing techniques to improve robustness. Andani and Nugraha integrated LVQ with Canny edge detection and Gray Level Co-occurrence Matrix (GLCM) for mango classification [6]. Although the testing accuracy was modest at 57%, the inclusion of texture-based features (GLCM) provided a more comprehensive representation of the fruit's surface. Furthermore, the role of distance metrics in classification cannot be overlooked. Research by Rizaldi et al. (2018) [7] and Jannah and Humaira (2019) [8] demonstrated that Euclidean Distance remains a gold standard for similarity measurements in pattern recognition, achieving success rates up to 87.84% in gait analysis. By synthesizing these findings, the current study proposes a refined approach by combining LVQ with Euclidean Distance to address the specific morphological challenges of chili pepper varieties in Kerik Village, Magetan.

2.2 Botanical Profile: Chili Peppers (Capsicum annuum)

Chili peppers, members of the Solanaceae family, are a cornerstone of Indonesian agriculture. Their economic significance is driven by high market demand and their extensive use in the culinary, pharmaceutical, and industrial sectors [3]. Botanically, chili varieties are distinguished by their size, shape, color, and pungency levels, which are determined by the concentration of capsaicinoids.

From a nutritional perspective, chili peppers are rich in carbohydrates, proteins, and essential vitamins (B, C, E, and K). They also contain potent bioactive compounds such as flavonoids and beta-carotene, which serve as natural antioxidants. For small-scale industries, such as sambal (chili paste) producers in East Java, the ability to distinguish between varieties like cabai rawit (bird's eye chili) and cabai keriting (curly chili) is vital, as any misidentification directly affects the chemical composition and heat profile of the final product.

2.3 Digital Image Processing in Automated Detection

In modern informatics, a detection system is defined as a computational framework that validates samples against predefined benchmarks to extract meaningful knowledge. This process is rooted in Digital Image Processing (DIP), which encompasses image enhancement, noise reduction, and feature extraction [9]. Mathematically, a digital image is a discrete representation of a continuous function $f(x, y)$, where x and y are spatial coordinates. The intersection of a row (N) and a column (M) defines a pixel, the fundamental unit of information containing intensity and color values. In the context of chili detection, DIP allows for the transformation of raw field photographs into structured feature vectors that can be processed by the LVQ algorithm.

2.4 Learning Vector Quantization (LVQ) Architecture

LVQ is a specialized class of Artificial Neural Networks (ANN) that utilizes a competitive, single-layer feedforward architecture. Unlike standard backpropagation, LVQ learns by shifting prototype vectors in the input space to better represent the boundaries between classes. The training mechanism is iterative and follows a precise mathematical protocol. The process begins with the initialization of weights (w), the learning rate (α), and the maximum epoch. For each training vector (x), the system identifies the winning unit the weight vector closest to the input based on the Euclidean metric:

$$Dj = \sqrt{\sum_{i=1}^{n}(x_i - w_{ij})^2} \text{ [10]}$$

The weights are then adjusted dynamically. If the winning prototype correctly represents the input's target class $T = C_j$, it is moved closer to the input:

$$w_{ji}(new) = w_{ji}(old) + \alpha\left[x_i - w_{ji}(old)\right] \text{ [10]}$$

The learning rate (α) is progressively reduced in each epoch to ensure convergence, preventing the system from overshooting the optimal solution.

2.5 Euclidean Distance and Performance Evaluation

Euclidean Distance serves as the primary metric for calculating the geometric separation between points in a multi-dimensional feature space. It is defined as the square root of the sum of squared differences between two vectors:

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \text{ [11]}$$

In certain scenarios requiring computational efficiency, researchers may also employ the City Block (Manhattan) Distance, which measures absolute differences:

$$d_1(x, y) = \sum_{i=1}^{n}|x_i - y_i| \text{ [11]}$$

The final stage of the research involves a rigorous accuracy assessment. This evaluation determines the system's reliability by comparing its automated predictions against empirical ground truth data. The accuracy percentage, which serves as the primary KPI for the proposed model, is calculated using the following ratio:

$$Accuracy = \left(\frac{Correct\ Classifications}{Total\ Samples}\right) x100\% \text{ [12]}$$

3. Method

The research follows a structured systematic flow to ensure the validity and reliability of the proposed chili detection system. The methodological framework, as illustrated in Figure 1, comprises several interconnected phases, beginning from the foundational literature study to the final performance evaluation.

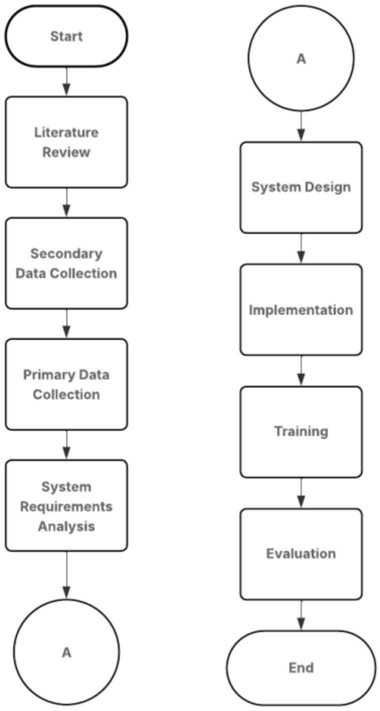

Figure 1. Research Methodology

The initial stage involves a comprehensive literature study to establish the theoretical framework and identify research gaps in the field of agricultural informatics and pattern recognition. This is followed by two distinct data collection phases: secondary data collection, which gathers existing theories and comparative studies, and primary data collection, where raw digital images of chili varieties are acquired directly from Kerik Village, Magetan. These datasets serve as the primary input for the subsequent computational processes.

Subsequently, a system requirements analysis is conducted to define the functional and non-functional specifications of the software. This phase informs the system design, where the architectural model and the integration of the Learning Vector Quantization (LVQ) algorithm are meticulously planned. In the system implementation phase, the proposed LVQ and Euclidean Distance methods are translated into executable code to build the automated classification engine.

The core of the technical process resides in the system recognition phase, where the model is trained to identify specific features of various chili types. To verify the effectiveness of this model, a rigorous system accuracy testing is performed, comparing the predicted outcomes against the ground truth. Finally, the research concludes with a conclusion phase, where the findings are synthesized to provide insights into the system's performance and its practical implications for the farming community.

4. Results and Discussion

4.1 Results

The proposed detection system was implemented using a web-based architecture to facilitate accessibility for both administrators and end-users. The dataset, comprising images of bird's eye chili (cabai rawit) and curly chili (cabai keriting) from Kerik Village, Magetan, was pre-processed using grayscale conversion to extract single-pixel intensity values from the original RGB format. A total of 80 images, each sized 377 x 275 pixels, were partitioned into 60 training samples and 20 testing samples.

The training phase utilized the Learning Vector Quantization (LVQ) algorithm to determine the optimal weight vectors, which subsequently served as the reference for the recognition process. To evaluate the effect of training intensity on system performance, three different iteration thresholds were tested: 500, 750, and 1,000 iterations.

4.2 Performance Analysis

The system's performance was evaluated by calculating the accuracy based on the proximity between input features and final weights using the Euclidean Distance metric. A comparative analysis of the accuracy results reveals a significant correlation between the number of iterations and the model's predictive reliability.

Table 1. Accuracy Across Ietrations

Evaluation Category	500 Iterations	750 Iterations	1,000 Iterations
Training Accuracy	56.67%	61.67%	71.67%
Testing Accuracy	55.00%	70.00%	85.00%

As seen in table 1, in contrast to the 500-iteration model, which yielded the lowest training accuracy of 56.67%, the 1,000-iteration model demonstrated a superior ability to converge toward optimal weight vectors, achieving a training accuracy of 71.67%. This trend indicates that increasing the iteration count allows the LVQ algorithm to refine the decision boundaries between curly and bird's eye chili varieties more effectively.

A critical comparison between training and testing performance shows that the system achieved its highest testing accuracy of 85.00% at 1,000 iterations. Interestingly, the testing accuracy consistently outperformed or remained comparable to the training accuracy across higher iterations. For instance, at 750 iterations, the testing accuracy reached 70.00%, significantly higher than the 61.67% achieved during the training phase. This suggests that the model maintains a strong generalization capability when identifying new, unseen images, provided that the training iterations are sufficient to stabilize the weight vectors.

4.3 Discussion

The performance of the proposed LVQ-Euclidean model for chili variety detection presents an insightful contrast when compared to existing literature in agricultural informatics. The peak testing accuracy achieved in this study, 85.00% at 1,000 iterations, aligns closely with the results reported by Azhari and Supratman (2021), who achieved 83.33% in pineapple classification [13]. This consistency suggests that the LVQ algorithm is highly effective for fruit-based morphological classification when provided with sufficient iterative training to stabilize weight vectors.

In contrast, the results of this study significantly outperform the rice variety classification research by Utomo (2016), which only reached 50.00% to 53.33% accuracy [14]. A critical factor contributing to this difference is the optimization of iterations; while Utomo’s model struggled with lower convergence, this research demonstrates that increasing iterations to 1,000 is vital to overcoming the low-accuracy threshold of 55.00% to 56.67% observed at only 500 iterations. This confirms that LVQ requires a higher computational "budget" to refine the decision boundaries between varieties with high visual similarity, such as cabai rawit and cabai keriting.

Furthermore, the integration of Euclidean Distance as a similarity metric proved to be a robust choice, mirroring the success seen in gait analysis by Jannah and Humaira (2019), which achieved 87.84% [8]. The high testing accuracy of 85.00% in this study indicates that the Euclidean metric effectively handles the grayscale intensity vectors derived from chili images, providing a more stable recognition result than the hybrid LVQ-Canny-GLCM method used by Andani and Nugraha, which only yielded 57.00% accuracy. This suggests that for localized datasets like those from Kerik Village, a streamlined approach focusing on optimized LVQ weights and Euclidean distance is more efficient than overly complex feature extraction techniques.

Ultimately, the observed phenomenon where testing accuracy (85.00%) exceeded training accuracy (71.67%) at 1,000 iterations provides a strong academic argument for the model's generalization capability. Unlike earlier studies that often suffered from overfitting, this research demonstrates a balanced learning curve, making it a reliable technological contribution to the smart farming initiatives in Magetan Regency

5. Conclusion

This study has successfully developed and evaluated an automated detection system for chili varieties by integrating the Learning Vector Quantization (LVQ) algorithm and Euclidean Distance. The experimental results indicate that the number of training iterations significantly influences the model's accuracy. The system achieved its peak performance at 1,000 iterations, yielding a training accuracy of 71.67% and a superior testing accuracy of 85.00%.

A comparative analysis reveals that the model effectively generalizes patterns from localized datasets in Kerik Village, outperforming several baseline studies in the agricultural domain. The contrast between training and testing outcomes further confirms that the system maintains high reliability without experiencing overfitting. In practice, this automated tool provides a strategic solution for farmers and the community to mitigate misidentification risks, thereby enhancing harvest consistency and service quality in the chili industry. Future research may focus on expanding the dataset and implementing real-time mobile integration to further support rural smart farming initiatives.

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