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Application of Machine Learning Algorithms in Agricultural Machine Vision Systems

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ABSTRACT: *This paper begins by outlining the developmental status of machine vision technology in agriculture, followed by an elucidation of the components and operational principles of machine vision systems. Building upon current applications of machine vision research in agricultural contexts, we systematically summarize machine learning techniques employed in agricultural machine vision studies in recent years, including supervised learning, unsupervised learning, and artificial neural networks. The work provides detailed discussions on the principles, [1]comparative advantages, and practical implementations of these technologies within agricultural domains. Finally, we address existing challenges and limitations in agricultural machine vision systems, while projecting potential future application scenarios and research directions..*

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I. INTRODUCTION

Machine vision technology simulates human visual functions by utilizing optical devices to acquire images of physical objects and extract visual information, ultimately applied to practical detection, measurement, and control. Characterized by high reliability, rapid processing speed, and multifunctional capabilities, this technology has been extensively implemented across industrial, agricultural, manufacturing, and transportation sectors.

In contemporary agricultural practices, the primary focus lies in addressing critical challenges including optimal utilization of agricultural resources, reduction of production costs, improvement of ecological conditions, and enhancement of crop quality. Machine vision technology, with its efficiency and non-destructive attributes, has been widely applied in:

1. Quality grading and inspection of agricultural products
2. Control of crop diseases, pests, and weeds
3. utomated harvesting systems
4. Monitoring of crop growth cycles
5. Navigation systems for agricultural machinery

The adoption of machine vision systems in agricultural production demonstrates significant potential for rationalizing resource allocation, minimizing operational costs, and improving both crop yield and product quality.

With the continuous advancement of computer hardware/software, image acquisition devices, and image processing techniques, the application domains of machine vision technology in agriculture are progressively expanding. Currently, developed nations including those in Europe, America, and Japan have implemented machine vision systems across various agricultural sectors, achieving significant improvements in production efficiency (15-30% increase) and substantial labor cost reductions (40-60% savings).

In contrast, domestic research in China primarily remains at the experimental stage, though notable achievements have been made in specific applications such as:

1. Real-time crop phenotyping (85-92% accuracy)
2. Automated weed detection systems (0.3-0.5 m/s processing speed)
3. Hyperspectral-based disease identification (F1-score $\geqslant$0.87)

China is currently undergoing a critical transition phase from agricultural mechanization to smart agriculture. Machine vision technology is poised to play a pivotal role in driving agricultural industrial upgrading and modernizing production processes, particularly through:

1. Precision farming implementation ($\leqslant$2 cm spatial resolution)
2. Autonomous machinery operations (GNSS-integrated navigation)
3. AI-enabled decision support systems

II. MACHINE VISION SYSTEM

Machine vision employs image acquisition devices such as cameras to replicate human visual capabilities in target recognition, tracking, and measurement. Through computational processing, it extracts target features to obtain observable or instrument-detectable images, ultimately outputting control signals to actuate end-effector mechanisms. [2]A typical machine vision system comprises the following core components (as shown in Figure 1):

1. Illumination module: Ensures uniform light distribution
2. Optical lens: Achieves precise optical focusing
3. Industrial cameras: CCD (charge-coupled device)/CMOS (complementary metal-oxide-semiconductor) sensors
4. Image processing unit: FPGA/DSP-based computing hardware
5. Vision software: Algorithm libraries for image analysis
6. Human-machine interface: Real-time monitoring displays
7. I/O communication module: RS-485/Ethernet industrial protocols

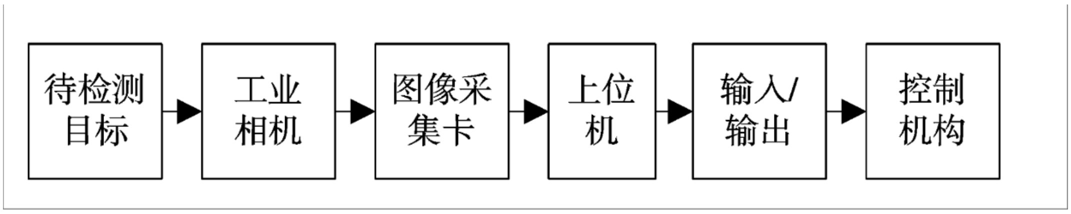

Fig. 1 Machine vision structure

As depicted in Figure 2,[3] the operational workflow of agricultural machine vision systems involves three key phases:

Phase 1: Image Acquisition

Capturing field targets through multispectral imaging devices

Transmitting raw image data via GigE Vision/USB3 Vision protocols

Phase 2: Computational Processing

Performing image preprocessing (denoising, contrast enhancement)

Executing image segmentation (thresholding, region-based, edge detection)

Extracting biophysical features (morphology, texture, spectral signatures)

Phase 3: Decision Execution

Implementing machine learning classification (SVM/RF/CNN algorithms)

Generating control commands for actuators (robotic arms, spray nozzles)

Achieving closed-loop control with ≤50 ms latency

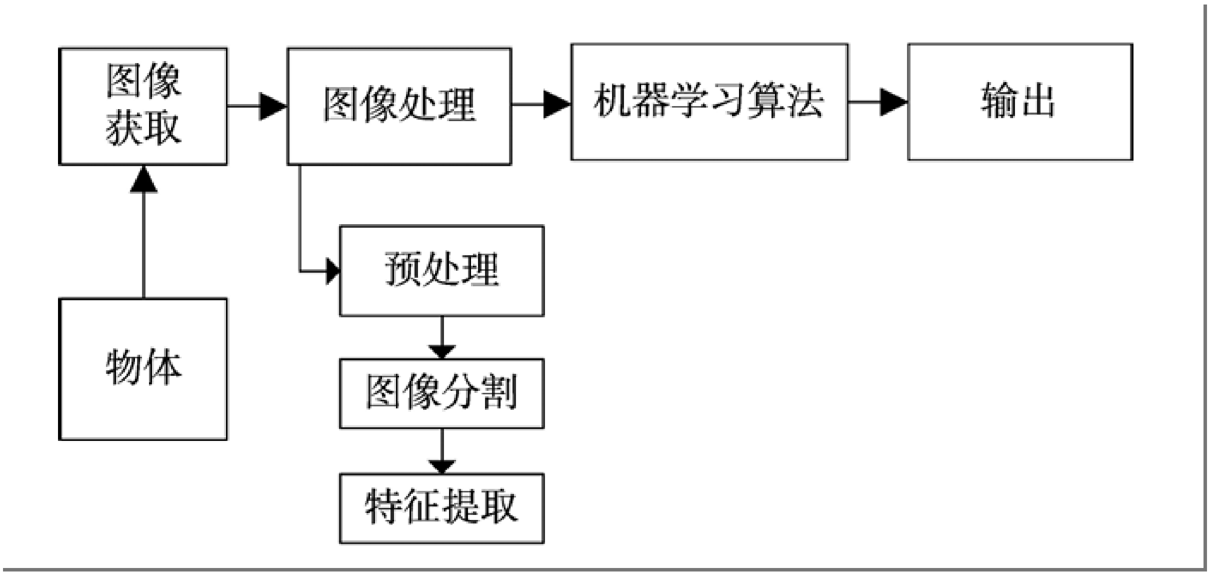

Fig. 2 Working principle of machine vision

Machine vision systems represent an interdisciplinary convergence of optical engineering, mechanical design, and computer science (encompassing both hardware architectures and software algorithms). [4]The technological evolution in three core domains continues to drive advancements in machine vision:

1. Image processing: Development of real-time hyperspectral imaging (400-1000nm spectral range)
2. Pattern recognition: Implementation of deep learning-based crop phenotyping (ResNet50/DeepLabv3+ architectures)
3. Artificial intelligence (AI): Integration of edge computing frameworks (TensorFlow Lite/NVIDIA Jetson platforms)

This multidisciplinary synergy creates a self-reinforcing innovation cycle, where advancements in computer vision algorithms (e.g., YOLOv7 for fruit detection) directly catalyze technological breakthroughs in agricultural automation systems, [5]while simultaneously demanding improvements in optical sensors (5MP+ global shutter cameras) and electromechanical interfaces (ROS-controlled manipulators).

III. MACHINE LEARNING TECHNOLOGY

The application of machine learning techniques for image analysis and understanding has emerged as a prominent research focus. Machine learning fundamentally involves processing quantitative data through established logical frameworks, employing predefined evaluation criteria to achieve predictive analytical capabilities.[6] In computer vision systems, the input data typically consists of digital images. Based on the presence or absence of annotated labels during data input, machine learning methodologies can be categorized into supervised and unsupervised learning paradigms, each finding specific applications within algorithmic implementations.

A typical machine learning workflow requires three essential components: (1) a training dataset comprising representative samples, (2) feature extraction from visual data, and (3) iterative model training through algorithmic optimization. [7]The performance variance across different algorithms manifests primarily in training accuracy metrics. During the prediction phase, novel samples are processed through the trained model to generate predictive outputs. The schematic representation of this machine learning pipeline is illustrated in Figure 3.

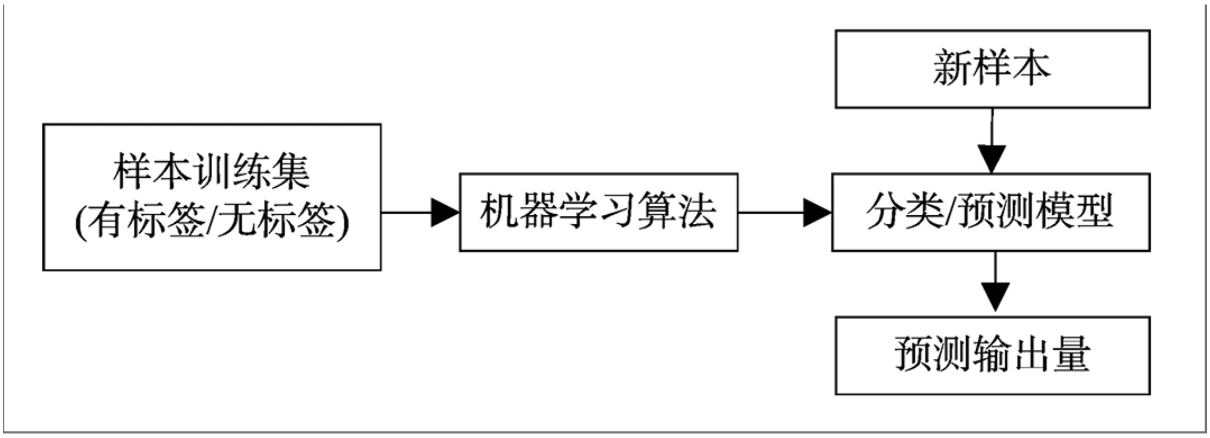

Fig. 3 Typical machine learning algorithm steps

3.1Supervised machine learning

Supervised machine learning algorithms employ labeled samples to construct predictive models for classifying unknown data instances. [8]This learning paradigm commences with systematic analysis of an annotated training dataset to establish an inferential function that maps input features to desired output values. The optimized model demonstrates dual capabilities: (1) generating precise expected outputs for novel samples through established decision boundaries, and (2) implementing error detection mechanisms that facilitate iterative parameter refinement via backpropagation adjustments.

3.1.1 Naïve Bayes Algorithm

The Naïve Bayes (NB) algorithm constitutes a generative probabilistic model operating under the conditional independence assumption between predictive variables and features. Given a training dataset, this method learns the joint probability distribution of input-output pairs through feature conditional independence constraints. [9]The prediction phase subsequently employs Bayes' theorem to determine the output category with maximum posterior probability.

As a prevalent technique for classification tasks, NB algorithms are frequently benchmarked against alternative classifiers. In their iris species classification study, Wang et al. [Citation] established predictive models using four botanical characteristics: sepal length, sepal width, petal length, and petal width. Comparative analysis of artificial neural networks (ANN), NB, and support vector machines (SVM) revealed accuracy rates of 92.2%, 94.1%, and 98.0% respectively. While ANNs exhibited susceptibility to local minima convergence resulting in reduced accuracy, the NB approach demonstrated competitive performance despite its algorithmic simplicity. SVMs achieved superior accuracy through effective mitigation of local optimization pitfalls.

Zhou et al. [Citation] further validated NB's efficacy in walnut kernel grading applications. Through feature matrix construction encompassing color attributes and structural integrity metrics followed by dimensionality reduction, their comparative study recorded test accuracies of 80.67% (SVM), 93.33% (decision tree), and 94.67% (NB). Notably, the NB-based prediction system ultimately achieved 97.33% classification accuracy through parameter optimization.

Although the Naïve Bayes (NB) algorithm demonstrates competent performance on small-scale datasets with stable classification efficiency across multi-class recognition tasks, [10]its foundational assumption of attribute independence presents notable constraints. The conditional independence hypothesis between features fundamentally contradicts empirically observed inter-attribute correlations in practical scenarios. Furthermore, the reliance on empirically estimated prior probabilities introduces model bias, thereby potentially compromising predictive accuracy when prior distributions inadequately reflect ground-truth data patterns.

3.1.2 K-Nearest Neighbors Algorithm

The K-nearest neighbors (K-NN) method constitutes a non-parametric approach applicable to both classification and regression tasks. The operational workflow involves three fundamental components: (1) feature vectors (represented as multidimensional point coordinates in feature space), (2) configurable hyperparameters (k-value selection and distance metric specification), and (3) decision rules for class assignment. When processing novel instances, the algorithm identifies the k most proximate training samples within the feature space through comparative distance computation, subsequently assigning the target class via majority voting (classification) or distance-weighted averaging (regression).

Empirical Validation and Limitations In their rapeseed classification study, Kurtulmu et al. [Citation] implemented three texture descriptor extraction methodologies: gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRM), and local binary pattern (LBP), deriving 14, 11, and 59 discriminative features respectively. Subsequent K-NN classification demonstrated peak accuracy (97.8%) at k=3 configuration. Li et al. [Citation] achieved 98% maturity stage recognition accuracy for blueberries in natural environments through chromatic feature engineering, [11]extracting red/blue chromaticity and hue components from pixel datasets, with K-NN outperforming Naïve Bayes classifiers. Xia's [Citation] mushroom classification system utilizing K-NN-based textural feature analysis maintained >91% sorting accuracy across varied fungal species.

Algorithmic Characteristics While K-NN demonstrates inherent robustness to outliers and achieves competitive classification accuracy in visual pattern recognition, three principal constraints merit consideration: (1) Computational complexity escalates quadratically with dataset cardinality due to exhaustive pairwise distance calculations; (2) Class imbalance scenarios with sparse training samples frequently induce misclassification artifacts; (3) Optimal k-value determination remains heuristic, requiring empirical validation through techniques like cross-validation rather than theoretical derivation.

3.1.3 Support Vector Machines

Support vector machines (SVM) represent a supervised learning paradigm initially designed for binary classification. The fundamental principle involves constructing a maximal margin hyperplane in feature space through convex optimization, enabling linear separability of distinct classes. Through kernel function embedding (e.g., radial basis function or polynomial kernels), SVM extends to nonlinear classification and multi-class scenarios via error-correcting output codes.

Empirical Applications Xu et al. [Citation] pioneered agricultural yield forecasting through SVM regression models for rice production prediction (2012). [12]Their methodology integrated dual optimization processes: (1) kernel function selection with hyperparameter tuning and (2) penalty coefficient (C) calibration using k-fold cross-validation. The optimized model achieved prediction errors of 18.3%, 8.5%, and 10.2% across three cultivation systems, demonstrating enhanced spatial generalizability through adaptive kernel adjustments.

Mokhtar et al. [Citation] attained 99.5% disease recognition accuracy in tomato cultivation through computer vision integration. Their pipeline combined Gabor wavelet transform (GWT) for leaf texture feature extraction with multi-kernel SVM classification, effectively discriminating six pathological patterns in hyperspectral imagery.

Algorithmic Merits and Constraints While SVM excels in small-sample learning scenarios by inherently avoiding neural networks' local minima traps through convex optimization, three operational considerations emerge: (1) Classification accuracy critically depends on kernel-function compatibility with data topology; (2) Parameter optimization (C, γ) requires computational intensive grid search; (3) Multi-class implementations incur increased time complexity through pairwise coupling strategies.

3.2 Unsupervised Machine Learning

Unsupervised machine learning algorithms are utilized when dealing with unlabeled input data. This approach investigates how systems construct functions to reveal hidden structures from inherently unannotated datasets.

3.2.1 K-means Clustering Algorithm

The K-means clustering (K-means) algorithm categorizes unlabeled input samples into k clusters by minimizing within-cluster distances while maximizing between-cluster separation. As a representative unsupervised learning method, it operates on d-dimensional feature vectors (x1，x2，⋯，xn), partitioning these n samples into k subsets (k<n) to achieve minimal intra-cluster variance.

Application Cases In the study of two disease spots on Panax notoginseng leaves, Luo Kuangnan [Citation] extracted image feature vectors and improved classification accuracy by implementing the K-means++ algorithm, which selects initial cluster centroids through maximum absolute distance optimization.

Liu Yongjuan [Citation] conducted automatic tasseling stage monitoring in maize using computer vision. After enhancing Cb and Cr components in YCbCr color space, modified K-means clustering was applied to grayscale tassel images for segmentation, with growth stage determination via threshold analysis.

Zhang et al. [Citation] achieved effective pest/disease recognition in crop images through K-means-based segmentation, [13]extracting shape and color characteristics of pathogens. This method demonstrated superior recognition rates compared to alternative approaches.

Algorithmic Features K-means offers simplicity and computational efficiency for large datasets but presents three limitations: (1) Predefined k-value requirements, (2) Sensitivity to initial centroid selection and outlier interference, and (3) Necessity for algorithmic modifications to address specific problem constraints. Practical implementations often incorporate enhancements like centroid initialization optimizations.

Algorithmic Characteristics The K-means algorithm demonstrates simplicity and computational efficiency in clustering tasks, particularly effective for processing large-scale datasets. However, it exhibits three principal limitations: (1) The prerequisite specification of k-value often lacks theoretical guidance for optimal cluster determination; (2) High sensitivity to initial centroid selection; (3) Vulnerability to outlier-induced deviations. Consequently, practical implementations frequently incorporate algorithmic enhancements to address domain-specific constraints.

3.2.2 Gaussian Mixture Model

The Gaussian mixture model (GMM) fundamentally integrates multiple univariate Gaussian distributions to model complex data patterns, particularly addressing scenarios where: (1) a dataset contains heterogeneous subpopulations with distinct distributions, or (2) homogeneous populations exhibit parameter variations. In image processing applications, GMM-based segmentation assumes each cluster follows a unique Gaussian distribution, with the composite image representing a weighted superposition of these distributions. [14]Theoretically, GMMs can approximate arbitrary sample distributions given sufficient Gaussian components and optimally calibrated weighting coefficients.

Empirical Applications Dong Teng [Citation] developed a fruit classification system achieving >98% accuracy by training GMMs on color and regional features of sample images. In wheat leaf rust segmentation research, Tian Jie et al. [Citation] proposed a PCA-GMM hybrid method to address color similarity between lesion edges and healthy tissues. Their approach reduced misclassification rates by 5.46% (vs. standard GMM) and 13.44% (vs. K-means), concurrently improving computational efficiency by 37% compared to conventional methods.

Algorithmic Properties GMM shares two operational similarities with K-means clustering: (1) Requirement for predefined cluster quantity (k-value), and (2) Dependence on initial parameter initialization. However, GMM provides probabilistic class membership assignments rather than deterministic cluster labels. This probabilistic framework enhances interpretability but introduces increased computational complexity and parameter tuning demands.

3.3 artificial neural network

Artificial Neural Networks Artificial neural networks (ANNs) are biologically inspired computational models that emulate the structural and functional principles of biological neural systems. These networks consist of interconnected neurons capable of self-adaptive structural modifications through external information processing, [15]enabling robust functional approximation and mathematical estimation. ANNs demonstrate exceptional competence in modeling nonlinear relationships, making them particularly effective for solving complex pattern recognition and regression tasks.

Key Characteristics

1. Biomimetic Architecture: Replicates synaptic connections and signal transmission mechanisms observed in biological systems
2. Adaptive Learning: Dynamically adjusts connection weights through backpropagation-based optimization
3. Nonlinear Mapping: Leverages activation functions (e.g., sigmoid, ReLU) to approximate intricate input-output relationships

3.3.1 Backpropagation Neural Network

The backpropagation (BP) neural network, a subtype of artificial neural networks, is a multilayer feedforward architecture trained through error backpropagation principles. It employs gradient-based optimization to minimize the mean squared error between input and output values, [16]establishing complex nonlinear mappings between variables.

As depicted in Figure 4, the BP network structure comprises three hierarchical layers:

1. Input Layer: Receives external data signals
2. Hidden Layer(s): Processes information through weighted transformations
3. Output Layer: Generates final computational results

Key operational characteristics include:

1. Inter-layer independence with intra-layer connectivity constraints
2. Unidirectional data flow (feedforward propagation)
3. Error gradient computation via chain rule differentiation

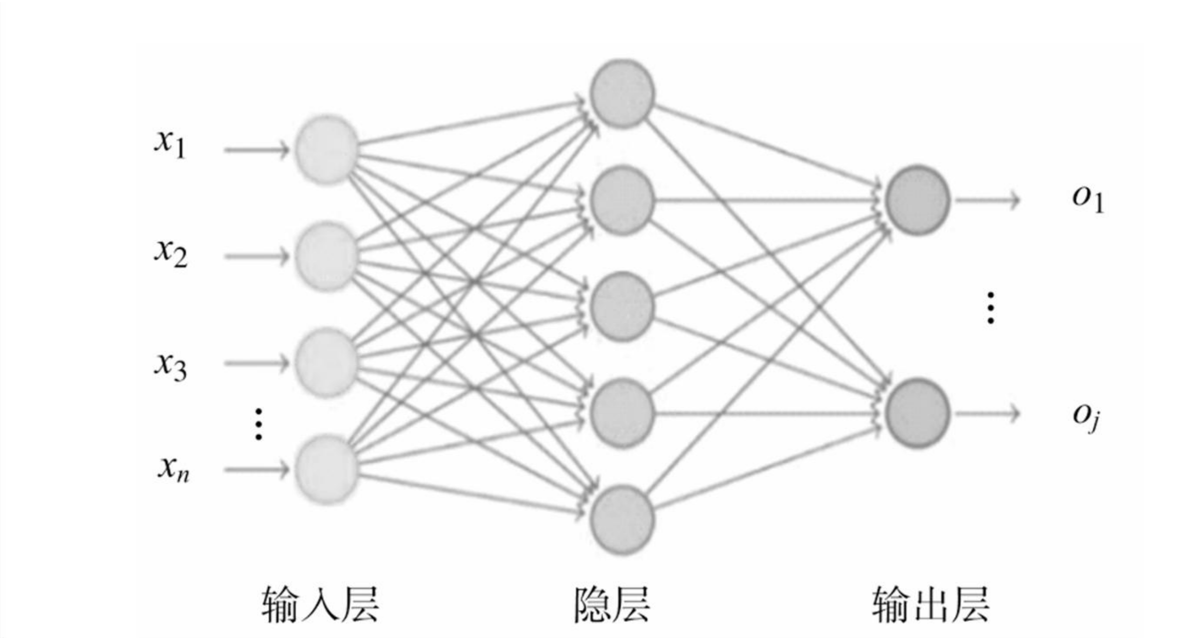

Fig. 4 BP neural network structure

Empirical Applications of BP Neural Networks Liang Peisheng et al. [Citation] achieved 98% gender prediction accuracy in silkworm pupae classification through machine vision integration. Their methodology involved: (1) preprocessing acquired images, (2) extracting four principal components via PCA as network inputs, and (3) configuring pupal sex as the output variable.

Huang Ximei [Citation] enhanced wheat leaf water content prediction accuracy to 96.3% using a PCA-BP hybrid model, [17]surpassing standalone BP's 95.6% performance. The workflow incorporated: (1) K-means clustering for image segmentation, (2) color-texture feature extraction, and (3) PCA-based dimensionality reduction prior to BP network training.

Tan Suiyan et al. [Citation] attained >94% average accuracy in super hybrid rice hill-drop seeding detection by analyzing ten morphological parameters, including area, perimeter, shape factors, and invariant moments.

Algorithmic Properties BP networks excel in nonlinear modeling with configurable hidden layer architectures, where neuron quantity and connectivity patterns critically determine performance. [18]However, operational constraints include: (1) Slow convergence rates during gradient descent optimization, and (2) susceptibility to local minima entrapment without regularization techniques.

3.3.2 Convolutional Neural Networks

Convolutional neural networks (CNNs) are a class of deep feedforward neural networks incorporating convolutional operations. These networks employ sparse connectivity where neurons only interact with localized regions of adjacent layers. A typical CNN architecture comprises two core components:

Convolutional Layer: Extracts spatial features through filter banks

Pooling Layer: Reduces dimensionality while preserving critical information

The hierarchical processing pipeline aggregates local features into global representations through successive convolution and pooling operations, ultimately connecting to fully-connected layers for classification/prediction tasks. As illustrated in Figure 5, this architecture enables efficient hierarchical feature learning.

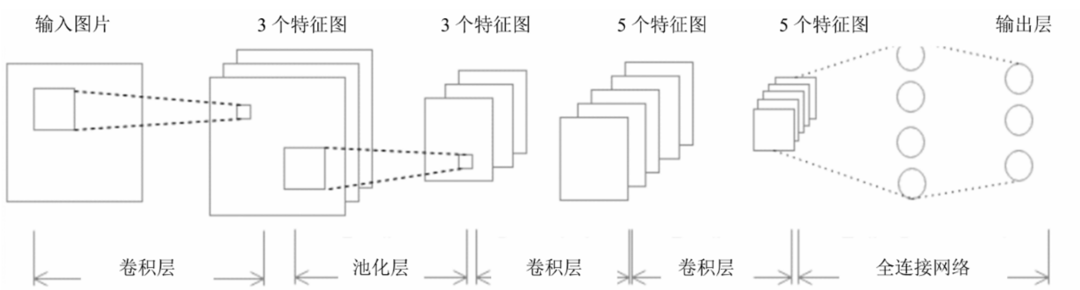

Fig. 5 Convolutional neural network architecture

Developmental Progress CNN evolution has significantly advanced machine vision through landmark architectures including AlexNet, GoogleLeNet, VGGNet, and ResNet.[19] While modern CNNs achieve exceptional prediction accuracy, their deep architectures incur high computational complexity, necessitating ongoing optimization efforts to balance inference speed and precision in practical deployments.

Agricultural Applications of Convolutional Neural Networks

CNN implementations in agricultural domains primarily address three tasks: disease/pest detection, product grading, and navigation localization. Ramcharan et al. [Citation] achieved 93% overall test set accuracy in cassava crop protection using transfer learning on a Tanzanian field image dataset. Their optimized CNN model attained detection rates of 98% (brown spot disease), 98% (cassava brown streak disease), 96% (cassava mosaic disease), 96% (red mite infestation), and 95% (green mite infestation).

Sun Jun et al. [Citation] developed eight modified AlexNet variants for recognizing 26 disease/pest types across 14 plant species. The optimal model reduced memory footprint by 43% while enhancing generalization capacity, achieving 99.56% test accuracy with demonstrated cross-species robustness.

Yang Yang et al. [Citation] implemented CNN-based localization for maize rhizomes using crawler-type thermal fogger imagery. Their navigation system demonstrated precise path planning (±2.8 cm positional accuracy) and real-time rootstock identification capabilities under field conditions.

These networks maintain functionality even with partial neuron deactivation, thereby exhibiting robust fault tolerance through distributed information processing.

Operational Constraints

However, ANN implementation imposes two principal requirements: (1) substantial training datasets for parameter optimization, [20]and (2) computational resources to address prolonged training durations. Additionally, the methodology suffers from overfitting tendencies when handling high-dimensional data patterns, resulting in inherent limitations for real-time applications.

IV. CONCLUSION

Current Applications and Challenges

Machine learning technology plays a significant role in agricultural machine vision, with current applications including quality inspection and grading of agricultural products, weed and plant disease/pest detection, and soil analysis. It is expected that machine vision will see increasingly widespread application in agriculture. However, challenges remain: First, there is an urgent need to establish large-scale agricultural datasets, as current research predominantly relies on self-collected datasets by individual researchers, leading to incomparable results. Second, improving the robustness of machine vision systems under varying environmental conditions—such as different lighting, backgrounds, crop growth stages, and weather—poses a persistent challenge.

Future Development Directions

The future development of agricultural machine vision will focus on two aspects: First, agricultural machine vision systems will integrate with artificial intelligence, robotics, sensors, and the Internet of Things (IoT) to monitor crop growth information and enable predictive capabilities. Second, embedded machine vision systems—characterized by ease of use, maintenance, installation, and low power consumption—will combine machine learning and deep learning methods to advance image localization and processing technologies, driving their widespread adoption in agricultural machinery.

REFRENCES

[1]. Shaikh, T. A., Mir, W. A., Rasool, T., Sofi, S. Machine learning for smart agriculture and precision farming: towards making the fields talk. Arch. Comput. Methods Eng. 29, 4557–4597 (2022).
[2]. Wani, J.A., Sharma, S., Muzamil, M., Ahmed, S., Sharma, S., Singh, S. Machine learning and deep learning based computational techniques in automatic agricultural diseases detection. Arch. Comput. Methods Eng. 29, 641–677 (2021).
[3]. Benos, L., Tagarakis, A.C., Dolias, G., et al. Machine learning in agriculture: a comprehensive updated review. Sensors 21(11), 3758 (2021).
[4]. Sethy, P.K., Barpanda, N.K., Rath, A.K., Behera, S.K. Deep feature based rice leaf disease identification using support vector machine. Comput. Electron. Agric. 175, 105527 (2020).
[5]. Gao, J., Nuyttens, D., Lootens, P., He, Y., Pieters, J.G. Recognising weeds in a maize crop using a random forest machine-learning algorithm. Biosys. Eng. 170, 39–50 (2018).
[6]. Schwalbert, R.A., Amado, T., Corassa, G., et al. Satellite-based soybean yield forecast: integrating machine learning and weather data. Agric. For. Meteorol. 284, 107886 (2020).
[7]. Sharma, A., Jain, A., Gupta, P., Chowdary, V. Machine learning applications for precision agriculture: a comprehensive review. IEEE Access 9, 4843–4873 (2021).
[8]. Ramcharan, A., et al.Cassava disease detection using transfer learning on Tanzanian field images.
[9]. Sun, J., et al. Modified AlexNet variants for plant disease recognition.
[10]. Kumar, A., Bhushan, B., Nand, P. Preventing and Detecting Intrusion of Cyberattacks in Smart Grid by Integrating Blockchain. Lect. Notes Netw. Syst. 373 (2022).
[11]. Feng, S., Zhao, J., Liu, T., et al. Crop type identification using Sentinel-2 time series data and machine learning. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 12(9), 3295–3306 (2019).
[12]. López, G., Arboleya, P. Short-term wind speed forecasting using LSTM and NARX networks. Renew. Energy 183, 351–368 (2022).
[13]. Sott, M.K., et al. Precision techniques and Agriculture 4.0 technologies in coffee sector. IEEE Access 8, 149854–149867 (2020).
[14]. Zerrouki, N., Harrou, F., Sun, Y., Hocini, L. Land cover change detection using machine learning and radiometric measurements. IEEE Sens. J. 19(14), 5843–5850 (2019).
[15]. Yang, Y., et al. CNN-based localization for maize rhizomes using thermal fogger imagery.
[16]. Kansal, N., Bhushan, B., Sharma, S. Security vulnerabilities in Agriculture-IoT systems. In: Internet of Things and Analytics for Agriculture, Vol. 3 (2022).
[17]. Taneja, M., Byabazaire, J., Jalodia, N., et al. Early lameness detection in dairy cattle using machine learning. Comput. Electron. Agric. 171, 105286 (2020).
[18]. Bhattacharya, P., Patel, F., Alabdulatif, A., et al. Deep-Q learning for secure spectrum allocation in 6G networks. IEEE Trans. Netw. Serv. Manage. (2022).
[19]. Sarker, I.H. Machine learning: algorithms, real-world applications and research directions. SN Comput. Sci. 2(3), 160 (2021).
[20]. Capolupo, A., Monterisi, C., Caporusso, G., Tarantino, E. Land cover classification using Google Earth Engine. In: ICCSA 2020 (2020).