ML and DL Techniques in Image Recognition

Explores CNNs, RNNs, LSTMs, Transfer Learning, SVMs, KNNs, and GANs. CNNs are most effective for spatial feature extraction. Transfer learning using VGG16 improves results. See 'Machine Learning Image Processing' diagram.

ML Techniques in Image Recognition

Core Algorithms

- **CNNs (Convolutional Neural Networks)**: Best for image classification with automatic feature extraction through convolution, pooling, and fully connected layers
- **Transfer Learning**: Uses pre-trained models (VGG16, ResNet, Inception) to reduce training time and improve performance
- Support Vector Machines (SVM): Effective in high-dimensional spaces for classification tasks
- **K-Nearest Neighbors (KNN)**: Simple baseline algorithm for non-linear image recognition
- RNNs/LSTM: Handle sequential data and temporal patterns in image captioning
- GANs: Generate synthetic training data for improved model stability

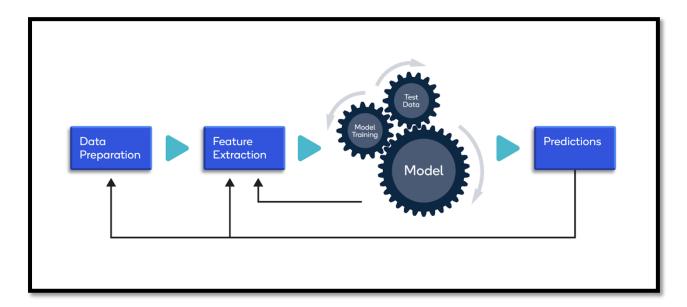


Figure 1 Machine Learning Image Processing (Kurama, 2024)

DL Core Technology and Techniques

Deep learning has revolutionized food identification, achieving state-of-the-art accuracy and efficiency in food image recognition and classification.

Key Techniques

CNNs (Convolutional Neural Networks)

- Architecture: Convolution layers → Pooling layers → Fully connected layers
- **Function**: Automatically learns spatial hierarchies and extracts food image features (edges, textures, shapes)
- Advantage: High accuracy and robustness in food recognition tasks

Transfer Learning

- Method: Fine-tune pre-trained models (ImageNet) for food-specific tasks
- Benefits: 10x faster training time and improved performance with limited labeled data
- Application: Leverages existing weights to boost food recognition accuracy

Ensemble Learning

- Approach: Combines multiple CNN architectures for enhanced performance
- Purpose: Overcomes individual model limitations through network diversity
- Result: Improved accuracy and robustness

Performance Results

- CNN + SVM combinations: >90% accuracy in multi-class food classification
- Proven effectiveness: Demonstrated across multiple research studies
- Continuous improvement: Advancing model architectures and training practices

Future Directions

- Robust models: Handle challenging conditions (occlusions, lighting variations)
- Real-time processing: Enable practical health monitoring applications
- Contextual integration: Incorporate environmental information for better recognition