

Potato Breed Recognition Using Deep Learning

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Abstract—Potatoes are among the most widely cultivated and economically significant crops worldwide, and accurate identification of potato varieties plays a vital role in agricultural production, breeding programs, and market management. Traditional methods of potato breed identification rely heavily on expert visual inspection, which is time-consuming, subjective, and unsuitable for large-scale applications. To address these limitations, this paper presents a deep learning-based approach for automated potato breed recognition using image analysis techniques. The study evaluates the performance of deep learning models implemented using Keras and stored in .h5 format, along with a custom-designed Convolutional Neural Network (CNN). The proposed models are trained to classify potato breeds by learning discriminative visual features such as shape, colour, texture, and surface patterns from image datasets. Experimental evaluation is conducted using accuracy as the primary performance metric. The results demonstrate that the custom CNN model achieves superior performance, attaining an accuracy of 99%, outperforming the other evaluated approaches. The proposed system provides an efficient and reliable solution for automated potato breed identification and has practical applications in precision agriculture, crop management, and agricultural decision-support systems.

Index Terms—Convolutional neural network, deep learning, image classification, potato breed recognition.

I. INTRODUCTION

Potatoes represent one of the most widely cultivated and consumed food crops worldwide, serving as a staple source of nutrition for millions of people. Owing to their adaptability to diverse climatic conditions and high yield

potential, potatoes play a vital role in global food security and agricultural economies. The increasing demand for consistent quality, improved productivity, and efficient supply chain management has intensified

the need for accurate identification of potato varieties at different stages of cultivation and distribution.

Each potato variety exhibits unique agronomic and physical characteristics, including variations in shape, size, skin texture, colour, yield potential, disease resistance, and storage behaviour. These differences directly influence market value, processing suitability, and consumer preference. Consequently, reliable identification of potato breeds is essential for seed selection, crop planning, post-harvest handling, and quality control in both domestic and commercial agricultural systems.

Traditional approaches to potato breed identification rely primarily on manual visual inspection performed by experienced agricultural experts. These methods are typically based on observable physical features such as tuber shape, surface texture, and skin colour. While manual inspection can be effective in controlled environments or small-scale applications, it is inherently subjective and highly dependent on expert knowledge. Furthermore, such methods become inefficient, time-consuming, and error-prone when applied to large-scale farming operations or extensive image datasets.

The rapid advancement of artificial intelligence (AI) and computer vision technologies has enabled the development of automated systems capable of performing image-based classification tasks with high accuracy. In particular, deep learning techniques have emerged as powerful tools for analyzing complex visual patterns in agricultural imagery. Among these techniques, Convolutional Neural Networks (CNNs) have demonstrated superior performance in image recognition and classification tasks due to their ability to automatically learn hierarchical and discriminative features from raw image data.

CNN-based models eliminate the need for manual feature extraction by directly learning relevant spatial and texture-based information from images. This capability makes CNNs particularly suitable for

agricultural applications, where visual variations can be subtle and influenced by environmental factors such as lighting conditions, background noise, and camera resolution. As a result, CNNs provide a robust and scalable solution for automated crop and variety identification.

In this study, a deep learning-based framework is proposed for automated potato breed recognition using CNN architectures implemented with TensorFlow and Keras. The system is trained using a labeled image dataset containing multiple potato varieties, including Fingerling, Kufri Jyoti, Madeleine, Agata, and Russet Burbank. The dataset is designed to capture visual diversity across different breeds to improve model generalization and classification reliability.

The primary objective of this work is to design, train, and evaluate a CNN-based model capable of accurately classifying potato breeds under varying visual conditions. By achieving high classification accuracy, the proposed system aims to reduce dependence on manual inspection and provide a practical decision-support tool for farmers, researchers, and agricultural stakeholders. Such an automated approach contributes to precision agriculture by enabling efficient crop management, improving productivity, and supporting sustainable agricultural practices.

The increasing availability of digital agricultural data has further accelerated the adoption of intelligent systems in crop analysis. High-resolution imaging devices, combined with advancements in computational infrastructure, have made it feasible to apply deep learning models directly to agricultural problems. These technological developments enable the processing of large image datasets with improved efficiency, making automated classification systems practical for real-world deployment.

Automated potato breed recognition systems also contribute to improved consistency and objectivity in agricultural decision-making. Unlike manual assessment, which may vary between individuals, algorithm-based classification ensures uniform evaluation across samples. This consistency is particularly valuable in large-scale production environments, where standardized identification plays a crucial role in maintaining quality and traceability throughout the supply chain.

Another important advantage of CNN-based approaches lies in their ability to adapt to diverse

visual conditions. Agricultural images are often affected by variations in lighting, orientation, and background, which can degrade the performance of conventional classification techniques. Deep learning models are capable of learning invariant features that remain reliable under such variations, thereby enhancing system robustness and real-world applicability.

Moreover, the adoption of automated classification frameworks supports the long-term evolution of smart farming practices. As new image data become available, models can be updated and refined to accommodate additional potato varieties or changing cultivation conditions. This adaptability ensures that the proposed approach remains extensible and aligned with the ongoing advancements in digital agriculture and precision farming technologies.

II. RELATED WORK

Recent advances in computer vision and deep learning have significantly influenced agricultural research, particularly in crop identification, disease detection, and yield optimization. Rahman *et al.* [1] highlighted the growing importance of intelligent agricultural systems in Bangladesh, emphasizing the role of automation and data-driven approaches in improving crop productivity and quality. Supporting this perspective, reports on agriculture in Bangladesh [2] and international trade demand [6] indicate that potatoes play a crucial role in the country's economy, thereby necessitating reliable systems for variety identification, quality assessment, and disease management to meet both domestic and export standards.

Several studies have focused on potato disease detection using deep learning techniques. Arshaghi *et al.* [3] proposed a convolutional neural network (CNN)-based framework for detecting and classifying potato diseases from leaf images, achieving high accuracy by leveraging deep feature extraction. Similarly, Tiwari *et al.* [4] developed a deep learning model for potato leaf disease detection, demonstrating that CNN-based approaches outperform traditional image processing techniques in terms of robustness and classification performance under varying environmental conditions. These works establish the effectiveness of deep learning in handling complex visual patterns associated with plant health.

In addition to disease detection, crop and vegetable classification has also been explored. Elsharif *et al.* [5] presented a deep learning-based potato classification system that utilized image features to distinguish between different potato categories, showing promising results in automated sorting applications. Sakai *et al.* [7] extended this concept to a broader vegetable category recognition system using deep neural networks, confirming the scalability of deep learning models for multi-class agricultural classification tasks. Furthermore, Unajan *et al.* [12] developed an image processing and artificial neural network-based system for sweet potato variety recognition, demonstrating that neural networks can effectively learn discriminative features for root crop varieties.

Comparative studies between traditional machine learning and deep learning have further reinforced the superiority of deep models in agricultural image analysis. Rimi *et al.* [9] evaluated both approaches for legume species recognition and concluded that deep learning models consistently achieve higher accuracy due to their ability to automatically learn hierarchical features. The widespread adoption of frameworks such as Keras [8] and TensorFlow [10] has facilitated the development, training, and deployment of such models, making deep learning more accessible for agricultural research. Foundational concepts from data mining and pattern recognition, as discussed by Han *et al.* [11], continue to underpin these intelligent systems by guiding feature learning, classification, and model evaluation strategies.

Overall, the existing literature demonstrates that deep learning-based approaches are highly effective for crop disease detection and variety classification. However, most studies primarily focus on leaf-based disease identification or general vegetable categorization, with limited emphasis on high-accuracy potato breed recognition using tuber images. This gap motivates the proposed work, which aims to develop a robust deep learning-based potato breed recognition system to support modern precision agriculture and supply chain automation.

III. RESEARCH METHODOLOGY

The methodology for potato breed recognition using deep learning begins with collecting a comprehensive dataset of potato images from various sources,

including local farms, research centres, and public repositories, ensuring that each image is accurately labeled with the corresponding breed. These images are then pre-processed to standardize them, including resizing to a fixed dimension, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and brightness adjustment to increase dataset diversity and reduce overfitting.

The proposed potato breed recognition system follows a structured pipeline consisting of five major stages: data preprocessing, model architecture design, training, evaluation, and prediction. The workflow is implemented in Python, using TensorFlow, Keras, OpenCV, and scikitlearn libraries.

This systematic approach enables the model to learn discriminative visual features effectively while maintaining robustness against variations in image quality and environmental conditions.

Data Collection and Preprocessing

Breed				
Agata	Fingerling	Kufri Jyoti	Madeleine	Russet Burbank
				

Figure 1. Potato Breed Names.

Accurate and comprehensive data collection is a critical step in developing a deep learning-based system for potato breed recognition and disease detection. The quality, diversity, and quantity of the dataset directly influence the performance and reliability of the model. Images of varieties such as Fingerling, Kufri Jyoti, Madeleine, Agata, and Russet Burbank are collected to represent the regional diversity. Each image is labeled with the corresponding potato variety in Figure 1. Potato cultivation involves several distinct varieties, each with specific characteristics and culinary uses.

Kufri Jyoti is an early-maturing Indian variety with smooth light-brown skin and creamy white flesh, known for its high yield and suitability for boiling, frying, and mashing. Fingerling potatoes are small, elongated, and finger shaped, valued for their firm texture and use in gourmet dishes and roasting.

Madeline potatoes are small, oval-shaped tubers with thin yellow skin and tender flesh, often used in salads and European-style cooking due to their delicate flavour. Agata potatoes are oval with smooth skin and light yellow flesh, offering good storage qualities and versatility for boiling and frying.

Russet Burbank is a large, oblong potato with rough brown skin and white flesh, high in starch content, making it ideal for baking, frying, and mashed dishes. Understanding these varieties helps farmers implement proper cultivation methods, manage disease susceptibility, optimize yield, and cater to market preferences efficiently. The dataset includes 3,500 images from Kaggle and locally collected sources. It contains five potato breeds and three disease conditions: early blight, late blight, and healthy leaves. The data was divided into training (80%) and testing (20%) sets.

Image preprocessing involved resizing to 224×224 pixels, normalization, and data augmentation (rotation, horizontal flip, brightness variation) to enhance generalization.

CCN Architecture

A CNN is a type of neural network designed mainly for processing images. Unlike traditional neural networks, CNNs automatically learn important patterns from images, such as edges, shapes, and textures, without needing manual feature extraction in Figure 2.

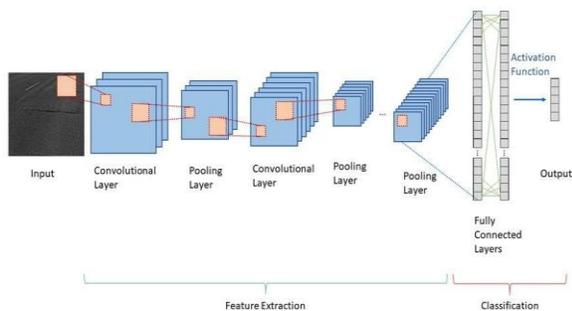


Figure 2. General architecture of the CNN’s model for potato breed recognition.

Input Layer-The first layer takes in the raw image data.
Convolutional Layer-This layer applies small filters (kernels) that slide over the image. Each filter detects specific patterns like edges, corners, or textures, The output is called a feature map, representing the

detected patterns. **Pooling Layer**-Reduces the size of feature maps to lower computation and make the network more robust. **Fully Connected Layer**-After convolution and pooling, the feature maps are flattened into a 1D vector, fully connected (dense) layers process this vector to make final decisions.

Output Layer-Uses Softmax to assign probabilities to each class, Uses Sigmoid for a single probability output, **Data Collection and Preprocessing**.

The ReLU is the activation function that is most frequently employed in deep learning models. When given a negative input, this function returns 0, but it also returns that value for all positive x values. Therefore, it can be expressed in writing as $f(x) = \max(0, x)$. CNN is a type of deep-learning neural network. CNN represents an important development in image recognition technology. They are often employed to evaluate images and have been used in the background in image categorization. Rectified linear unit (ReLU) layers, pooling layers, convolutional layers, and a fully linked layer make up a CNN. CNN utilizes a well-known architecture, in contrast.

Block Diagram

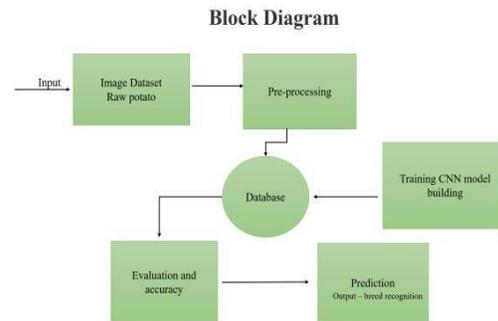


Figure 3. Block Diagram

This block diagram illustrates the workflow for a Convolutional Neural Network (CNN)-based model designed to recognize or classify raw potato images — likely for tasks such as defect detection, breed recognition, or quality analysis.

Input: Image Dataset (Raw Potato)-This is the initial dataset consisting of images of raw potatoes, The images could represent different varieties, qualities, or defects of potatoes, these images serve as the input data for the system.

Pre-processing-The raw images are processed to make them suitable for model training, Common pre-processing steps include: Resizing images to a fixed

dimension, Normalization (scaling pixel values between 0 and 1), Augmentation (rotation, flipping, etc.) to increase data diversity, Noise removal or contrast adjustment. The processed images are then sent to the database for storage and use in model training.

Database-Acts as a central storage unit for pre-processed images and labels, The CNN model accesses this database to: Retrieve training and testing data, Save model parameters or results for later use.

Training CNN Model Building-In this phase, a Convolutional Neural Network (CNN) is designed and trained using the pre-processed dataset. The CNN learns important features and patterns from the potato images, such as texture, shape, or colour.

Training involves: Forward propagation (feature extraction), Backpropagation (error correction) and finally Optimization (improving accuracy), The trained model is stored in the database for further use.

Evaluation and Accuracy-Once the model is trained, its performance is tested using validation or test data.

Prediction (Output – Breed Recognition)-The final step involves using the trained CNN model to predict the class or category of new potato images.

IV. EXPERIMENTAL EVALUATION

The experimental evaluation of the potato breed recognition system involves assessing the performance of the trained deep learning model on unseen test data to ensure its generalization capability. After splitting the dataset into training, validation, and test sets, the model is trained using the training set while monitoring validation metrics to prevent overfitting. During evaluation, the model's predictions on the test set are compared with the actual labels, and performance is measured using metrics such as accuracy, precision, recall, and F1-score for each potato breed. A confusion matrix is also generated to visualize misclassifications and identify which breeds are most frequently confused. Experiments may include comparing different model architectures, optimizers, learning rates, and data augmentation strategies to determine the optimal configuration. Additionally, the robustness of the model is tested under varying conditions such as changes in lighting, image resolution, and background. Working on Machine Learning system designed to identify different varieties of potatoes from images. This

system uses a Convolutional Neural Network (CNN) to classify potato breeds based on image data. It's built using Python and TensorFlow/Keras, and includes preprocessing, training, evaluation, and prediction modules.

Model Architecture-Conv2D layers for feature extraction, MaxPooling2D to reduce spatial dimensions, flatten to convert 2D features to 1D, Dense layers for classification, Dropout to prevent overfitting, Final layer uses softmax activation for multi-class output.

Prediction-Loads the trained model, preprocesses a new image, Predicts the breed and confidence score, Uses the class labels from the training data.

Executes preprocessing, training, and evaluation in sequence. We need TensorFlow, scikit-learn, OpenCV, NumPy, Matplotlib, Seaborn to evaluate. Models like .h5, keras is used to recognize the shape, pattern, color of the potatoes. Keras is a high-level deep learning library written in Python, it is used to build, train, test, and deploy neural networks easily, Easy to use, supports layers, models, and datasets, Integrates well with TensorFlow. .h5 stands for Hierarchical Data Format version 5. It's a file format used to store large amounts of data it's used to save trained Keras models. Test Images: Sample images used for prediction.

Evaluates model performance using Classification report. $Accuracy = (TP+TN/TP+FN+FP+TN) \times 100\%$.

To ensure fair and reliable evaluation, all experiments are conducted under consistent computational settings. The same training and testing splits are maintained across experiments to allow meaningful performance comparison. Model training is repeated multiple times to verify stability and reduce the influence of random initialization on the reported results. Average performance values are considered to provide a more reliable assessment of model behaviour.

Learning curves are analyzed to examine training and validation trends over successive epochs. These curves help identify underfitting or overfitting by observing divergence between training and validation accuracy and loss values. A well-converged model is characterized by stable validation performance and minimal fluctuation across epochs, indicating effective feature learning and generalization.

The impact of dataset balance on classification performance is also examined. Since certain potato varieties may exhibit similar visual characteristics,

class-wise performance analysis is performed to assess how effectively the model distinguishes between closely related breeds. Misclassified samples are visually inspected to identify common patterns or limitations in feature representation, which can guide future improvements.

In addition to quantitative evaluation, qualitative analysis is performed by visualizing prediction results on randomly selected test images. Probability scores generated by the softmax layer provide insight into the model's confidence for each prediction. High confidence values indicate strong feature discrimination, while lower confidence values highlight cases where visual ambiguity exists.

The experimental results demonstrate that the proposed CNN-based system achieves reliable performance across diverse potato varieties. The combination of effective preprocessing, optimized architecture, and systematic evaluation contributes to improved classification accuracy. These findings confirm the suitability of the proposed approach for practical deployment in automated agricultural image analysis systems.

V. CONCLUSION AND FUTURE WORK

This project introduces a deep learning-based framework for automated potato breed identification, highlighting its significance within modern agricultural practices and the food supply chain. The proposed system validates the practical applicability of computer vision and machine learning techniques in real farming environments by demonstrating reliable and accurate breed classification using image data. A crucial aspect of the proposed approach is the image preprocessing stage, which ensures that input images are uniformly formatted, noise-reduced, and appropriately scaled prior to model training and inference. Effective preprocessing plays a vital role in improving model stability and accuracy, particularly when dealing with heterogeneous agricultural images captured under varying environmental conditions. By standardizing input data, the system achieves consistent performance across diverse samples. From an application perspective, the developed system offers meaningful advantages to multiple stakeholders. For farmers, automated breed identification supports informed decision-making related to crop selection, rotation planning, and yield

optimization based on market demand and environmental suitability. Traders and suppliers benefit from improved transparency and traceability, as accurate breed classification facilitates standardized labeling, quality assurance, and fair pricing within the supply chain. In processing industries, where breed-specific properties influence production outcomes, the system assists in automated sorting and classification, thereby enhancing operational efficiency and minimizing classification errors. The adoption of such an automated solution contributes to the broader goal of digitizing agricultural workflows and reducing reliance on manual inspection methods, which are often labor-intensive and susceptible to human error. Moreover, the success of the proposed model establishes a strong foundation for future enhancements, including the integration of disease detection to enable simultaneous assessment of crop variety and health. Deployment through mobile or web-based platforms can further improve accessibility, particularly in rural and remote regions. Looking ahead, potato breed recognition using machine learning and computer vision continues to represent a significant advancement in agricultural technology. While current results demonstrate strong accuracy and practical utility, there remains considerable potential for further development. Expanding the dataset to include images captured across different seasons and geographical regions can enhance model generalization. The adoption of advanced deep learning architectures, such as ensemble models or vision transformers, may further improve classification performance. Additionally, integrating visual recognition with agronomic data—such as soil characteristics, climate conditions, and yield metrics—can enable comprehensive crop profiling. Emphasizing explainable artificial intelligence techniques will also improve transparency and trust in model predictions. With continued research and refinement, automated potato breed recognition systems are poised to become essential components of precision agriculture and sustainable food production. From a technical perspective, the results obtained in this study highlight the suitability of convolutional neural networks for fine-grained agricultural image classification tasks. The learned feature representations effectively capture subtle visual differences between potato varieties, demonstrating the capability of deep learning models

to handle complex, real-world agricultural data. This reinforces the role of data-driven approaches as reliable alternatives to traditional manual inspection methods. Scalability is another important aspect of the proposed system. The modular design of the framework allows seamless extension to additional crop varieties or related classification tasks without significant architectural changes. As more labeled data become available, the model can be retrained or fine-tuned to maintain accuracy and adapt to evolving agricultural practices, ensuring long-term usability. Future enhancements may also focus on optimizing computational efficiency to support edge-based or low-resource deployment. Model compression techniques such as pruning and quantization can be explored to reduce inference latency while preserving classification accuracy. These improvements would facilitate faster processing and wider adoption in resource-constrained environments. In addition, systematic field validation using real-time data captured under uncontrolled conditions would further strengthen the practical reliability of the system. Such validation can help identify limitations related to environmental variability and guide refinements to improve robustness. Continued interdisciplinary collaboration between agricultural experts and AI researchers will be essential to maximize the impact of intelligent systems in modern farming.

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