Environment and Ecology 42 (2B) : 775—779, April—June 2024
Article DOI: https://doi.org/10.60151/envec/KRWS4781
ISSN 0970-0420

Agricultural Advancements through Machine Learning Technologies

Parul Sharma, Pawanesh Abrol

Received 27 December 2023, Accepted 2 April 2024, Published on 3 June 2024

ABSTRACT

Machine learning, a subset of artificial intelligence, is revolutionizing agriculture by enabling enhanced crop monitoring, disease detection, and yield prediction. Its application extends to precision farming, where it aids in optimizing irrigation, fertilization, and harvesting by analyzing large datasets from mobile phones, sensors and satellite images. It has played a crucial role in identifying and categorizing different types of plants. Specifically, Convolutional Neural Networks (CNN), a deep learning technology within ML, are employed to classify plant species based on images. In the present research work, we have employed machine learning for the classification of citrus species using Convolutional Neural Networks (CNNs). A dataset has been developed with images of fruits and leaves from ten citrus species. We have utilized transfer learning with architectures like Mobile Net, Alex Net, and Goog Le Net. The study demonstrates that combining multiple plant components in CNN analysis improves classification accuracy, with leaves providing more reliable results than fruits. This approach signifies a major advancement in agricultural technology, allowing for more precise and efficient farming practices. The findings indicate that expanding the dataset and incorporating more plant structures could further refine these models. This research highlights the potential of machine learning in agriculture, particularly in enhancing species classification, which is crucial for sustainable and productive farming.

Keywords Agriculture, Citrus Classification, Convolutional Neural Network (CNN), Machine learning, Plant species classification.

INTRODUCTION

Machine learning (ML), a crucial branch of artificial intelligence, involves the use of algorithms and statistical models to enable machines to improve their performance on a specific task through experience. This technology has revolutionized numerous industries, ranging from healthcare to finance, by providing efficient solutions to complex problems. In the context of botany and agriculture, machine learning plays a crucial role. With its capabilities in classification, categorization, regression, decision-making, and more, machine learning has become an integral part of various agricultural research fields (Mourtzinis *et al.* 2021). In the realm of plants, it has demonstrated success in recognizing species, detecting diseases,

Parul Sharma[1], Pawanesh Abrol[2]*

[2]Professor and Head
[1,2]Department of Computer Science and IT, University of Jammu, J&K 180006, India

Email: pawanesh.abrol@gmail.com
*Corresponding author

evaluating health status, monitoring growth, predicting yield, and more. While several user-friendly mobile applications have been developed for these purposes, they often lack accuracy and comprehensive coverage of plant species (Singh *et al.* 2018).

ML encompasses a variety of algorithms and methodologies used to enable computers to learn from and make decisions based on data. Broadly categorized into supervised, unsupervised, and reinforcement learning (Fig. 1), each type has distinct approaches and applications (Sarker 2021). In supervised learning the labelled dataset is used to train the machine to learn patterns. The machine is provided with the correct answers (labels), and the algorithm makes predictions or decisions based on the data. It is further divided into classification and regression tasks. Classification algorithms, such as Support Vector Machines (SVM) and Logistic Regression, categorize data into predefined groups, while regression techniques like Linear and Polynomial Regression predict continuous numerical values. Unsupervised Learning, in contrast, deals with unlabeled data. The algorithm tries to learn the underlying structure from the data without any explicit instructions on what to look for. Dimensionality reduction and clustering are two primary unsupervised learning strategies. Dimensionality reduction, with methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), simplifies data by reducing the number of variables under consideration. Clustering algorithms, such as K-means and Partitioning Around Medoids (PAM), group datasets into clusters based on similarity without any prior knowledge of the group identities. Reinforcement learning is characterized by trial and error, where an agent learns to make decisions by performing actions and observing the results, which typically come in the form of rewards or punishments. The learning process is guided by the pursuit of positive reinforcement and the avoidance of negative outcomes. This form of learning can be highly effective in dynamic environments where the algorithm must make a sequence of decisions that lead to a long-term goal.

Applications of ML in agriculture

Machine learning in agriculture is revolutionizing the way we approach farming and food production, offering innovative solutions to age-old challenges. This technology leverages data and algorithms to predict outcomes, optimize processes, and make more informed decisions, significantly impacting the agricultural sector (Kamilaris and Prenafeta-Boldú 2018). In the following sections, the paper will discuss the diverse and impactful applications of machine learning in the agricultural domain. Following this comprehensive overview, the focus will shift to a specific case study: 'Applying ML in Agriculture: A Study on Citrus Species Classification.' This case study will illustrate the practical implementation of machine learning techniques in agriculture, demonstrating their effectiveness in real-world scenarios and providing insights into future applications and

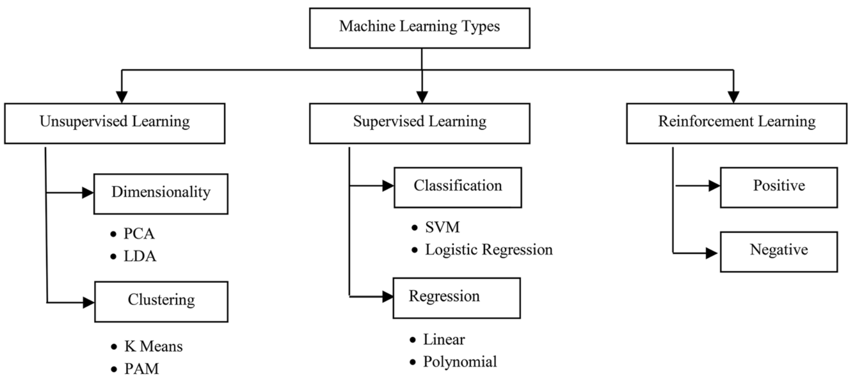

Fig. 1. Types of machine learning.

developments in the field.

Crop monitoring and management

One of the primary applications of machine learning in agriculture is in crop monitoring and management. Machine learning has been beneficial for increasing crop productivity by evaluating yield estimations, yield mapping, and matching supply with demand (Amatya *et al.* 2016). Detection and identification of crop disease is one of the most important research projects works that concerns agriculture. It deals with automatic disease identification in the crops (Pantazi *et al.* 2017). The presence of weeds poses a challenge to crop growth and productivity, and their detection and species identification are complex but necessary tasks for maintaining crop health (Pantazi *et al.* 2016).

Quality assessment

The quality assessment of crops, another key application of machine learning, is vital for improving yields and minimizing losses through accurate classification and estimation of crop quality (Zhang *et al.* 2017). With this technology, farmers and agronomists can detect subtle changes in plant physiology, which are indicative of stress or disease, long before they are visible to the human eye (Gupta *et al.* 2023).

Precision agriculture

This is another vital area, which uses machine learning to adapt farming practices to the specific needs of each crop and land. This approach leads to more efficient use of resources such as water, fertilizers, and pesticides, reducing environmental impact while maximizing yield (Sharma *et al*. 2021). ML models analyze data on soil composition, topography, and historical crop performance to make recommendations for planting, irrigation, and harvesting. This level of precision was previously unattainable and can significantly increase the efficiency and sustainability of farming operations (Blesslin Sheeba *et al.* 2022). Furthermore, machine learning aids in the automatic classification and identification of different crop or plant species, showcasing its wide-ranging impact on agricultural efficiency and effectiveness (Grinblat *et al.* 2016, Sharma and Abrol 2022-2023).

Animal welfare

Machine learning also helps in observing animals for diseases and health monitoring. Animal behavior can be closely observed for their well-being as suggested by (Zhang *et al.* 2021). Livestock production. Animal produce like eggs, milk, yarn. Can be observed for its quality and quantity assessment (Bao and Xie 2022).

Machine learning is not just for specific farm tasks; it also helps in other important ways. It can be used to keep an eye on the environment and manage resources better, like using less water and making farming more eco-friendly (Virnodkar *et al.* 2020). It's also great for improving how food gets from farms to stores, making this process more efficient and reducing waste. Plus, it helps farmers understand what the market needs and what people want to buy, guiding them to make smart choices about what to grow and how much (Tirkolaee *et al.* 2021).

Applying ML in agriculture: A study on citrus species classification

After exploring the diverse applications of machine learning in agriculture, ranging from crop management to environmental monitoring, it becomes evident how this technology can be applied to specific agricultural challenges. One such application is demonstrated in our research, which focuses on the classification of citrus species using machine learning techniques (Sharma and Abrol 2023). The methodology employs of Convolutional Neural Networks (CNNs) to analyses two critical components of plants which are leaves and fruits. The process (Fig. 2), commences with an extensive dataset collection phase. A new dataset has been curated that is composed of two distinct plant components: Fruits and leaves from ten closely resembling citrus species. This was followed by the creation of a segmented dataset, curated by isolating the subjects and removing backgrounds from the original images. Both the original and segmented datasets, now enriched with fruit and leaf images, are assimilated and individually processed as input. In this stage, six different input combinations were created: Original images of fruits, leaves, and both, as well as the segmented versions of these categories. These inputs were then channeled through a CNN

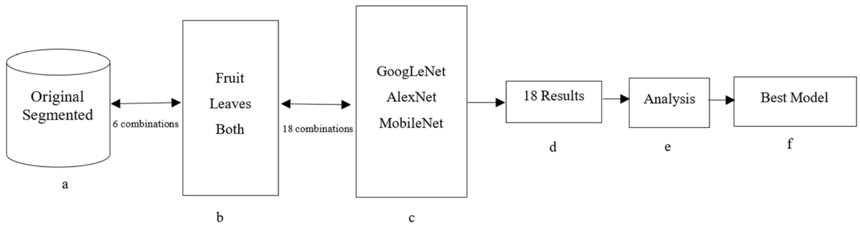

Fig. 2. Flowchart of research work (a) Dataset creation, (b) Input to CNN, (c) Three CNN models, (d) Results obtained from 18 experiments, (e) Result analysis and (f) Selection of best model for citrus species classification (Sharma and Abrol 2023).

model that leverages transfer learning techniques, incorporating established architectures like Mobile Net, Alex Net, and Goog Le Net. This method resulted in eighteen distinct experimental setups, each representing one of the six input combinations processed through each CNN architecture. These setups were then accurately assessed for their performance and accuracy. The analysis was dedicated to determining the most effective combination of dataset and CNN architecture that would result in the highest accuracy for classifying citrus species.

For this research, datasets were created with the images of leaves and fruits of ten citrus plants from the orchards of SKUAST- Jammu. The names of species are *Citrus × sinensis* (sweet orange), *Citrus nobilis* x *citrus deliciosa* (kinnow), *Citrus jambhiri* (rough lemon), *Citrus pseudolimon* (hill lemon), *Citrus × paradisi* (grapefruit), *Citrus maxima* (pomelo), *Citrus limetta* (sweet lime), *Citrus × aurantiifolia* (lime), × *Citrofortunella microcarpa* (calamondin orange), and *Citrus limon* (lemon). Subsequently, the images underwent a segmentation process to generate a segmented dataset, enhancing the clarity and focus of the samples for further analysis.

Summary of the present research work: Three salient observations have emerged from the data analysis. Firstly, even though citrus species closely resemble each other, the results obtained, when its multiple organs are combined for CNN, are comparable to a similar type of work conducted earlier on diverse range of plant species. The effectiveness of CNN in distinguishing between closely related citrus species emphasizes its potential in detailed plant classification tasks. Secondly, in the study focusing on citrus plants, it was observed that leaf-based data yielded higher classification accuracy compared to fruit-based data. This finding highlights the distinct advantages of using leaf characteristics for more accurate identification in citrus species. Thirdly, the method of combining features from various components of plant within the Convolutional Neural Network (CNN) framework showed enhanced classification accuracy compared to using a single component in CNN. This approach highlights the effectiveness of integrating multiple data sources for more precise plant species identification. The implications of these findings suggest promising avenues for future research.

These results not only demonstrate the practical applications of machine learning in agriculture but also pave the way for more refined and efficient approaches to plant classification, contributing to the broader goal of enhanced crop management and sustainable farming practices.

CONCLUSION

Machine learning in agriculture has become evident and this technology is driving significant transformations within the farming industry. The paper has highlighted the significant role of machine learning in revolutionizing various aspects of agriculture, from crop management to animal welfare. The present research work on citrus species classification using ML techniques demonstrates the practical applicability of these technologies and also highlights their potential in enhancing citrus plant species classification accuracy with the help of multiple components of plants. As machine learning technology develops, it is expected to bring even more innovative solutions to traditional agricultural challenges. Future research should build on these initial findings to discover new ways to make farming more efficient and advanced. Integrating machine learning into agriculture is a continuing process with great potential for significant and positive changes in the field.

REFERENCES

Amatya S, Karkee M, Gongal A, Zhang Q, Whiting MD (2016) Detection of cherry tree branches with full foliage in planar architecture for automated sweet-cherry harvesting. *Biosystems Engineering* 146: 3–15. DOI: https://doi.org/10.1016/j.biosystemseng.2015.10.003

Bao J, Xie Q (2022) Artificial intelligence in animal farming: A systematic literature review. *Journal of Cleaner Production* 331: 129956. DOI: https://doi.org/10.1016/j.jclepro.2021.129956

Blesslin Sheeba T, Anand LDV, Manohar G, Selvan S, Wilfred CB, Muthukumar K, Padmavathy S, Ramesh Kumar P, asfaw BT (2022) Machine learning algorithm for soil Analysis and classification of micronutrients in IoT-Enabled Automated Farms. *Journal of Nanomaterials* pp 1–7. DOI: https://doi.org/10.1155/2022/5343965

Grinblat GL, Uzal LC, Larese MG, Granitto PM (2016) Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture* 127: 418–424. DOI: https://doi.org/10.1016/j.compag.2016.07.003

Gupta T, Titunath, Jain V (2023) Plant disease detection using Deep Learning. *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings* pp 202–206. DOI: https://doi.org/10.1109/icscss57650.2023.10169268

Kamilaris A, Prenafeta-Boldú FX (2018) Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture* 147: 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Mourtzinis S, Esker PD, Specht JE, Conley SP (2021) Advancing agricultural research using machine learning algorithms. *Scientific Reports* 11(1): 17879. DOI: https://doi.org/10.1038/s41598-021-97380-7

Pantazi X.-E, Moshou D, Bravo C (2016) Active learning system for weed species recognition based on hyperspectral sensing. *Biosystems Engineering* 146 : 193–202. DOI: https://doi.org/10.1016/j.biosystemseng.2016.01.014

Pantazi XE, Tamouridou AA, Alexandridis TK, Lagopodi AL, Kontouris G, Moshou D (2017) Detection of silybum marianum infection with Microbotryum silybum using VNIR field spectroscopy. *Computers and Electronics in Agriculture* 137: 130–137. DOI: https://doi.org/10.1016/j.compag.2017.03.017

Sarker IH (2021) Machine learning: Algorithms, Real-world Applications and Research Directions. *SN Computer Science* 2(3): 160. DOI: https://doi.org/10.1007/s42979-021-00592-x

Sharma A, Jain A, Gupta P, Chowdary V (2021) Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access* 9: 4843–4873. DOI: https://doi.org/10.1109/access.2020.3048415

Sharma P, Abrol P (2022) Analysis of Multiple Component Based CNN for Similar Citrus Species Classification. In. Gunjan VK, Zurada JM (Eds.), Modern Approaches in Machine Learning & Cognitive Science: A Walkthrough. (2022nd ed., Vol. 1027, pp. 221–232). Springer, Cham.

Sharma P, Abrol P (2023) Similar plant species classification with Dual input transfer learning models. *Applied Biological Research* 25(3): 361–371. DOI: https://doi.org/10.5958/0974-4517.2023.00040.x

Singh AK, Ganapathysubramanian B, Sarkar S, Singh A (2018) Deep learning for plant stress phenotyping: Trends and Future Perspectives. *Trends in Plant Science* 23(10): 883–898. DOI: https://doi.org/10.1016/j.tplants.2018.07.004

Tirkolaee EB, Sadeghi S, Mooseloo FM, Vandchali HR, Aeini S (2021) Application of machine learning in supply chain management: A comprehensive overview of the main areas. *Mathematical Problems in Engineering* pp 1-14. DOI: https://doi.org/10.1155/2021/1476043

Virnodkar SS, Pachghare VK, Patil VC, Jha SK (2020) Remote sensing and machine learning for crop water stress determination in various crops: A critical review. *Precision Agriculture* 21(5): 1121–1155. DOI: https://doi.org/10.1007/s11119-020-09711-9

Zhang M, Li C, Yang F (2017) Classification of foreign matter embedded inside cotton lint using short wave infrared (SWIR) hyperspectral transmittance imaging. *Computers and Electronics in Agriculture* 139 : 75–90. DOI: https://doi.org/10.1016/j.compag.2017.05.005

Zhang S, Su Q, Chen Q (2021) Application of machine learning in animal disease analysis and prediction. *Current Bioinformatics* 16(7) : 972–982. DOI: https://doi.org/10.2174/1574893615999200728195613