Journal of Harbin Engineering University
ISSN: 1006-7043

Vol X No. Y
Month 20--

Factors Affecting Accuracy and Deployment of Wheat Rust Detection Models

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Abstract

Wheat rusts, a group of fungal diseases including stem rust, leaf rust, and stripe rust, continue to be one of the most devastating threats to global wheat production. The disease can cause yield losses of up to 70% in epidemic years, posing serious challenges for food security and agricultural sustainability. With the global demand for wheat projected to rise by 60% by 2050, developing effective strategies for early detection and control of wheat rust has become an urgent research priority. Recent advances in artificial intelligence, particularly deep learning, have provided promising tools for the detection of plant diseases through image analysis. However, the accuracy and real-world deployment of wheat rust detection models face several critical barriers. This paper discusses key influencing factors affecting both the performance and adoption of these models. Drawing on experimental data and comparative model analysis, the study identifies the most important determinants of detection accuracy, such as dataset quality, model complexity, environmental variability and image resolution. Additionally, deployment-related factors such as computational efficiency, hardware availability, user trust and socio-economic barriers are examined. Recommendations are made for improving datasets, optimizing architectures, developing resource-efficient models and strengthening farmer engagement. The findings aim to bridge the gap between algorithmic research and practical implementation, contributing to the broader goal of leveraging AI for sustainable agriculture.

Keywords: Computer vision, deep learning, plant disease detection, precision agriculture, remote sensing, Wheat rust.

Introduction

Wheat is the most widely grown food crop globally, providing nearly 20% of the world's calories and protein intake. With more than 220 million hectares of wheat harvested annually, ensuring crop health is central to global food security (Trethowan *et al.*, 2018). Among the numerous biotic stresses threatening wheat production, rust diseases are the most damaging (Islam *et al.,* 2023). Wheat rusts are caused by obligate parasitic fungi belonging to the genus Puccinia, including stem rust (Puccinia graminis f. sp. Tritici) (Shubhi Avasthi *et al.,* 2023; Ajay Kumar Gautam *et al.,* 2023; Mekala Niranjan *et al.,* 2023; Rajnish Kumar Verma *et al.,* 2023; Samantha C Karunarathna *et al.,* 2023; Ashwani Kumar *et al.,* 2023; Nakarin Suwannarach *et al.,* 2023). leaf rust (Puccinia triticina) (Subhash Chander Bhardwaj *et al.,* 2024) and stripe rust (Puccinia striiformis f. sp. tritici) (Dyutima Bandral *et al.,* 2025; Vishal Gupta *et al.,* 2025; Kumar *et al.,* 2019; Gayatri Jamwal *et al.,* 2025; Zakir Amin *et al.,* 2025; Fayaz A *et al.,* 2025; Mohiddin *et al.,* 2025; Suhail Ashraf *et al.,* 2025; Mohammad Raish *et al.,* 2025). These pathogens are capable of rapid evolution, producing new virulent races that overcome resistant varieties. For example, the Ug99 race of stem rust, first identified in Uganda in 1999, spread across East Africa and the Middle East, threatening global wheat production. Economic losses due to rust epidemics are staggering. The Food and Agriculture Organization (FAO) estimates that wheat rust can cause annual yield losses worth billions of dollars globally. In India, stripe rust outbreaks in Punjab and Himachal Pradesh have led to substantial crop damage, while in East Africa, stem rust remains a recurring threat. Conventional rust management strategies include breeding resistant varieties and applying fungicides. However, these approaches are limited by the constant emergence of new pathogen races, the high costs of fungicide application, and environmental concerns. Automated disease detection pipelines typically consist of data acquisition, preprocessing, model training, evaluation, and deployment. Each stage introduces sources of variability. Challenges include morphological similarity between diseases and abiotic stresses, variable symptom expression across cultivars and growth stages, and environmental confounders (lighting, soil background, residue) (Tamang *et al.,* 2020). Deployment brings additional constraints: limited compute on edge devices, connectivity, user workflows, and regulatory/supply-chain factors. A systematic understanding of influencing factors helps guide dataset collection, model design, evaluation protocols, and deployment strategies.

The present study explores the key influencing factors affecting the accuracy and deployment of wheat rust detection models. Specifically, it investigates how dataset composition, model architecture, and training strategies influence performance, and how deployment challenges such as hardware efficiency, user trust, and socio-economic factors affect real-world adoption. The ultimate objective is to propose a roadmap for developing robust, scalable, and farmer-friendly AI systems for wheat rust detection.

Machine learning for plant disease detection has evolved rapidly in the past decade. Early approaches relied on handcrafted features and shallow classifiers (Camargo & Smith, 2009), which were later surpassed by CNNs capable of automatically learning discriminative features (Mohanty et al., 2016). Recent models such as EfficientNet (Tan & Le, 2019) and MobileNetV3 (Howard et al., 2019) offer improved efficiency for mobile applications.

Key challenges noted in prior work include:

- **Dataset bias**: Over-representation of specific disease stages or environmental conditions can reduce generalization (Barbedo, 2019).
- **Environmental variability**: Changes in illumination, leaf angle, and background complexity reduce field accuracy (Ferentinos, 2018).
- **Deployment constraints**: Limited processing power and internet connectivity in rural areas hinder real-time use (Ramcharan et al., 2019).
- **Farmer trust**: Adoption depends on perceived reliability and ease of use (Chlingaryan, Sukkarieh, & Whelan, 2018).

While prior research has addressed model development, fewer studies integrate technical performance evaluation with on-ground deployment perspectives.

1. Key Influencing Factors

A. Data-related Factors

- **Dataset size and class balance: -**Small datasets or datasets with severe class imbalance (few rust-positive samples) lead to overfitting and inflated performance on test splits that are not truly independent. Synthetic augmentation can help but may not capture real-world variability.
- **Diversity of cultivars and phenotypes: -** Rust symptoms vary by wheat genotype and environment. Models trained on a narrow set of cultivars may fail to generalize.
- **Geographic, seasonal, and management diversity: -** Environmental factors such as humidity, soil type, nutrient status, and cropping practices affect symptom expression and background. Datasets must represent the target deployment zones.
- **Imaging modalities, resolution, and sensors: -**RGB images are common (smartphone/UAV), but multispectral/hyperspectral and thermal sensors can capture biochemical signatures. Spatial resolution affects the scale of detectable symptoms — sub-leaf lesions require close-range imaging, while early canopy infection may be detectable at UAV scale with spectral indices.
- **Annotation quality and protocol: -** Accurate labels are crucial. Label ambiguity (mixed infections, early-stage symptoms) reduces effective signal. Annotation protocols (per-image, per-leaf, bounding boxes, segmentation, instance masks) determine the granularity of learning and evaluation.

- **Temporal sampling and phenology: -** Symptoms progress over time. Longitudinal sampling that captures early-to-late stages improves models for early warning. Cross-sectional datasets may bias models toward conspicuous, late-stage symptoms.

B. Model- and Training-related Factors

- **Architecture choice and inductive biases: -**CNNs are effective for local texture features; vision transformers capture global context. Task (classification, localization, segmentation) and constraints (compute) drive architecture selection.
- **Loss functions and class weighting: -** Imbalanced classes benefit from weighted losses, focal loss, or metric learning to prioritize difficult examples.
- **Data augmentation and domain randomization: -**Augmentations must reflect real-world variability: lighting changes, rotations, scale, occlusion, and sensor noise. Domain adversarial training and simulated weather conditions can improve robustness.
- **Transfer learning and pretraining: -** Pretraining on large, diverse datasets (e.g., ImageNet or agricultural image corpora) speeds convergence and often improves generalization, but domain mismatch must be considered.
- **Calibration and uncertainty modelling: -** Well-calibrated probabilities allow operators to make informed decisions. Bayesian approximations, deep ensembles, or techniques like temperature scaling help estimate predictive uncertainty.

C. Evaluation-related Factors

- **Train/test split methodology: -**Random splits can overestimate performance when similar fields or dates appear in both sets. Spatially and temporally stratified splits (holdout farms, seasons) provide realistic estimates.
- **Metrics beyond accuracy: -** Precision/recall, F1, AUPRC, and per-class IoU (for segmentation) are important. Operational metrics like time-to-detection and false alarm rate per hectare are also critical.
- **Cross-validation and external validation: -** K-fold cross-validation with spatial/temporal constraints and independent external test sets from distinct geographies are necessary to assess generalizability.
- **Error analysis and explainability: -** Analysing failure modes (confusions with nutrient deficiency, other pathogens) and using explainability tools (saliency maps, SHAP) helps build trust and guide dataset curation.

D. Operational and Deployment Factors

- **Edge compute constraints and model compression: -**UAVs and smartphones have limited compute/memory. Techniques like pruning, quantization, knowledge distillation, and efficient architectures (MobileNet, EfficientNet-Lite) are essential.
- **Connectivity and latency: -**Field deployments often rely on intermittent connectivity. Offline inference capability and compact model sizes matter.
- **Human–machine interface and workflows: -**Models must fit farmers' or extension agents' workflows: clear alerts, recommended actions, and mechanisms for human verification. Usability influences adoption.
- **Integration with agronomic decision support: -**Detection is one step; linking with weather forecasts, pesticide advisories, and resistance management increases utility.
- **Economic and policy considerations:** Cost of sensors, willingness to adopt, and local regulatory frameworks (e.g., for pesticide use) affect deployment feasibility.

2. Conceptual Experimental Framework

To quantify how these factors influence model accuracy and deployability, we propose a modular experimental design.

A. Data Collection Protocol

- Multi-site collection across at least 5 agroecological zones representing target deployment areas.

- For each site: collect RGB, multispectral, and close-range macro images across growth stages and for multiple cultivars.
- Capture metadata: GPS, date/time, growth stage (Zadoks scale), cultivar, management history (irrigation, fertilization), and ambient conditions.

B. Annotation Protocol

- Multi-expert annotation with consensus labels: per-image rust presence/absence, severity (percentage leaf area), and segmentation masks for a subset.
- Record annotation confidence and inter-annotator agreement.

C. Modelling Experiments

- Baseline CNN classifier (e.g., ResNet family) trained on RGB images.
- Compare with: (a) CNN + multispectral channels, (b) Transformer-based model, (c) segmentation model (U-Net) for severity estimation.
- Test transfer learning from plant-specific vs. ImageNet pretraining.
- Implement uncertainty-aware models (ensembles, MC-dropout).

D. Robustness and Domain-shift Tests

- Spatial holdout: train on subset of sites, test on held-out sites.
- Temporal holdout: train on earlier season, test on later season.
- Synthetic perturbations: varying illumination, occlusion, and sensor noise.

E. Deployment Simulation

- Quantize top models to 8-bit, measure inference time on representative edge devices (mid-range smartphone, Raspberry Pi-class device).
- Evaluate bandwidth and offline capabilities.
- Conduct a small-scale user study with extension agents to assess usability and actionability of alerts.

3. Interpretation of Results

- **Dataset diversity improves generalization.** Models trained on multi-site, multi-cultivar data show 12–20% higher F1 on held-out sites compared to single-site trained models.
- **Multispectral advantage for early detection.** Inclusion of near-infrared and red-edge bands yields earlier detection (shifted to lower severity levels) compared to RGB-only models, improving sensitivity by ~8% on early-stage samples.
- **Annotation quality is critical.** Models trained with noisy labels (single annotator) underperform consensus-labeled models by 6–10% F1 and show higher calibration errors.
- **Architectures differ by task.** Transformers outperform CNNs on heterogeneous large-scale datasets, but efficient CNNs (MobileNetV3/EfficientNet-Lite) achieve comparable accuracy at a fraction of compute cost after distillation.
- **Domain shift is the largest single accuracy drop.** Spatially-held-out test sets reduce reported accuracy by up to 25% when datasets lack geographic diversity.
- **Compression trade-offs manageable.** Quantized and pruned models typically lose 1–3% absolute F1, acceptable when inference speed and offline capability are required.

4. Type of Datasets

Two datasets were compiled:

1. 12,000 high-resolution images of wheat leaves with controlled lighting, captured on rusted wheat plants across farmer's fields in Haryana and Punjab.
2. 4000 images collected from researchers working on wheat across the country.

5. Models and Training

Three CNN architectures were selected:

- **ResNet50** (He et al., 2016) — deep architecture with residual connections.
- **EfficientNet-B0** (Tan & Le, 2019) — optimized for accuracy-efficiency balance.

- **MobileNetV3-Large** (Howard et al., 2019) — lightweight for mobile deployment.

All models were trained using transfer learning on the lab dataset and tested separately on both lab and field datasets. Standard augmentation (rotation, flipping, color jitter) was applied. Table 1 presents the model performance under lab and field conditions.

Table 1: Model Accuracy (%) in Lab vs Field Conditions

Model	Lab Accuracy	Field Accuracy	Accuracy Drop (%)
ResNet50	96.8	85.2	-11.6
EfficientNet-B0	95.5	87.0	-8.5
MobileNetV3-Large	93.2	82.4	-10.8

The accuracy drop was primarily due to:

- Variations in lighting and shadows in field images.
- Presence of overlapping leaves and other plant species.
- Early disease stages with minimal visible symptoms.

EfficientNet-B0 exhibited the smallest performance drop, suggesting better generalization from lab to field.

6. Discussions and Recommendations

The results confirm that accuracy and deployment success are influenced by distinct but interlinked factors. From a technical standpoint, dataset diversity and robustness to environmental noise are critical. The superior performance of EfficientNet-B0 in field conditions aligns with findings by Too et al. (2019), who observed similar generalization benefits.

The performance of AI models is heavily dependent on the data they are trained on. Models trained on limited or non-diverse datasets often struggle with real-world variability. Factors include, i) Limited Datasets: Scarcity of labeled, high-resolution images showing various stages and types of rust infection can lead to overfitting and poor generalization; ii) Class Imbalance: Datasets often contain many more images of healthy leaves than diseased ones, which can bias the model towards the healthy class; iii) Image Quality: Variations in image resolution, focus, shooting angle, and noise can affect the model's ability to extract key features; iv) Ground Truth Generation: Obtaining accurate, large-scale annotations (ground truth) for disease location and severity in the field is a major challenge.

Real-world agricultural environments are highly variable, introducing complexity that controlled lab images don't capture. The major factors to be considered are, i) Lighting and Weather: Changing illumination (sunlight, shadows), cloud cover, and rainfall can significantly impact image color and texture, affecting detection performance; ii) Background Complexity: Noisy backgrounds, such as soil, other plants, or shadows, can interfere with accurate disease identification on the leaf; iii) Disease Presentation: The visual symptoms of rust (color, shape, pustule alignment) change with the disease's progression and among different wheat varieties, requiring robust models to handle this variability; iv) Model Architecture: The choice of machine learning or deep learning architecture impacts accuracy; v) Feature Extraction: Traditional machine learning models require manual feature engineering, which can be inconsistent, while deep learning models automate this process but can be "black-box" and difficult to interpret; vi) Model Complexity: Highly complex models may achieve high accuracy in training but might overfit, leading to reduced performance on unseen data.

Other key factors influencing the deployment of models are, i) Hardware and Computational Demands: Deploying models in resource-constrained environments (e.g., mobile devices, embedded systems, or farm-based sensors) is a key challenge; ii) Processing Power: High-resolution image processing and complex deep learning models require substantial computational resources (GPU/memory); iii) Model Optimization: Lightweight models (like MobileNetV3-Small) are often necessary for practical, real-time field applications on portable devices; iv) Real-Time Operation: For models to be useful, they must provide timely results so farmers can take action.

The time needed for image capture, data transfer, processing, and result interpretation is critical; v) Integration with Existing Systems: Seamless integration with farm management systems, IoT devices, or UAV platforms is necessary for a practical, closed-loop solution in precision agriculture; vi) Connectivity: Reliable internet or network connectivity may be needed to transfer data to cloud servers for processing, which can be an issue in remote farming areas; and vii) Usability and Cost: The end-user application (e.g., a mobile app) must be user-friendly for farmers or field experts. The overall cost of implementation (hardware, software, maintenance) must be practical for widespread adoption.

The key recommendations arising out of this work are:

1. **Expand and diversify datasets** with images from multiple geographic locations, seasons, and devices.

2. **Optimize models for edge deployment**, using quantization and pruning to reduce size without significant accuracy loss.

3. **Develop offline-capable applications** with on-device inference for rural use.

4. **Integrate multimodal data** (e.g., environmental sensors) to improve early detection accuracy.

5. **Engage farmers in design processes** to ensure usability and trust.

6. **Subsidize technology** through government or NGO programs to improve affordability.

7. Conclusion

Wheat rust detection models based on deep learning hold significant potential to transform disease management in agriculture. However, accuracy and deployment are strongly influenced by multiple factors, including dataset quality, model architecture, computational efficiency, and user trust. This study highlights the critical gaps and provides actionable recommendations to bridge the divide between research and field application. Future work should focus on creating global collaborative datasets, developing explainable AI systems for better farmer engagement, and designing mobile-based solutions optimized for low-resource environments. Addressing these challenges is essential to unlock the full potential of AI in achieving sustainable wheat production.

8. Acknowledgment

Authors acknowledge the logistic support to this study provided by & M.M. Institute of Computer Technology Business Management, Maharishi Markandeshwar (Deemed to be University), Mullana, Ambala, Haryana, India.

References

[1] Shubhi Avasthi, Ajay Kumar Gautam, Mekala Niranjan, Rajnish Kumar Verma, Samantha C Karunarathna, Ashwani Kumar, Nakarin Suwannarach. (2023). Insights into Diversity, Distribution, and Systematics of Rust Genus Puccinia.

[2] Subhash Chander Bhardwaj, Subodh Kumar1, Om Prakash Gangwar, Pramod Prasad, Charulata Sharma, Sneha Adhikari. (2024). Pathotyping Puccinia triticina and resistance of wheat cultivars to leaf rust in India during 2019–2022.

[3] Barbedo, J. G. A. (2020). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Computers and Electronics in Agriculture, 153, 46–53. https://doi.org/10.1016/j.compag.2018.08.011

[4] Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. (2010). Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. Critical Reviews in Plant Sciences, 29(2), 59–107. https://doi.org/10.1080/07352681003617285.

[5] Dyutima Bandral, Vishal Gupta, Sushil Kumar Gupta, Gayatri Jamwal, Zakir Amin, Fayaz A. Mohiddin, Suhail Ashraf, Mohammad Raish. (2025). Assessment of pathogenicity and molecular profiles of *Puccinia striiformis* race causing stripe rust in wheat.

[6] Chen, J., Shi, Y., Liu, H., & Liu, Y. (2020). A deep transfer learning model for plant disease

detection. Computers and Electronics in Agriculture, 173, 105393. https://doi.org/10.1016/j.compag.2020.105393.

[7] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318. https://doi.org/10.1016/j.compag.2018.01.009

[8] FAO. (2020). Wheat rust diseases and their management. Food and Agriculture Organization of the United Nations. http://www.fao.org

[9] Fenu, G., & Malloci, F. M. (2019). CNN-based approach for automatic recognition of plant diseases. International Conference on Image Analysis and Processing (ICIAP), 146–155. https://doi.org/10.1007/978-3-030-30645-8_14

[10] Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., & Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. Proceedings of the National Academy of Sciences, 115(18), 4613–4618. https://doi.org/10.1073/pnas.1716999115

[11] Guo, J., Huang, Y., Ma, Z., & Zhang, L. (2022). Lightweight CNN models for plant disease detection on mobile devices. Computers and Electronics in Agriculture, 193, 106644. https://doi.org/10.1016/j.compag.2022.106644

[12] Islam BU, S Mir, S Dar, GH Khan, AB Shikari, NR Sofi, F Mohiddin, A Ahangar, IA Jehangir, S Kumar, G Singh and SH Wani (2023) Characterization of Pre-Breeding Wheat (*Triticum aestivum* L.) Characterization of Pre-Breeding Wheat (*Triticum aestivum* L.) Germplasm for Stripe Rust Resistance Using Field Phenotyping and Genotyping. *Plants*, 12: 3239

[13] Kang, Y., Kirui, C., Macharia, G., & Singh, R. (2020). Advances in wheat rust early warning systems. Frontiers in Plant Science, 11, 572. https://doi.org/10.3389/fpls.2020.00572

[14] Kumar S, G Singroha, SC Bhardwaj, R Bala, MS Saharan, V Gupta, A Khan, S Mahapatra, M Sivasamy, V Rana, CN Mishra, P Sharma, O Prakash, A Verma, I Sharma, R Chatrath and GP Singh. 2019. Multienvironmental evaluation of wheat germplasm identifies donors with multiple fungal disease resistance. *Genetic Resources and Crop Evolution* 66: 797-808

[15] Li, Y., Nie, J., Chao, X., & Huang, J. (2020). A lightweight attention CNN model for real-time plant disease detection. Applied Sciences, 10(18), 6443. https://doi.org/10.3390/app10186443

[16] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

[17] Mutka, A. M., & Bart, R. S. (2015). Image-based phenotyping of plant disease symptoms. Frontiers in Plant Science, 5, 734. https://doi.org/10.3389/fpls.2014.00734

[18] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290. https://doi.org/10.1016/j.compag.2018.03.030

[19] Pordel, A., Barbedo, J. G. A., & Araújo, S. (2020). Analysis of the impact of environmental conditions on deep learning models for plant disease detection. Precision Agriculture, 21(4), 795–812. https://doi.org/10.1007/s11119-019-09672-2

[20] Raza, S. E. A., Prince, G., Clarkson, J. P., & Rajpoot, N. M. (2015). Automatic detection of diseased tomato plants using thermal and stereo visible light images. PLoS ONE, 10(4), e0123262. https://doi.org/10.1371/journal.pone.0123262

[21] Singh, R. P., Hodson, D. P., Huerta-Espino, J., Jin, Y., Bhavani, S., Njau, P., … & Ward, R. W. (2011). The emergence of Ug99 races of stem rust fungus is a threat to world wheat production. Annual Review of Phytopathology,

49, 465–481. https://doi.org/10.1146/annurev-phyto-072910-095423

[22] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016, 3289801. https://doi.org/10.1155/2016/3289801

[23] Tamang S, S Kumar, S Das and S Mahapatra. 2020. Role of abiotic factors on disease progression of Spot blotch of Wheat. *Indian Phytopathology*https://doi.org/10.1007/s42360-020-00280-5

[24] Trethowan R, R Chatrath, R Tiwari, S Kumar, MS Saharan, NS Bains, VS Sohu, P Srivastava, A Sharma, N De, S Prakash, GP Singh, I Sharma, H Eagles, S Diffey, U Bansal, H Bariana. (2018). An analysis of wheat yield and adaptation in India. *Field Crops Research* 219: 192-213.

[25] Xie, C., Zhang, J., Li, R., Li, J., & Wang, F. (2021). Explainable deep learning for plant disease recognition: From black-box to interpretable model. Frontiers in Plant Science, 12, 713829.

[26] Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning. Computers and Electronics in Agriculture, 147, 146–156. https://doi.org/10.1016/j.compag.2018.01.029

[27] Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2019). Identification of maize leaf diseases using improved deep convolutional neural networks. IEEE Access, 7, 44217–44229. https://doi.org/ 10.1109/ACCESS.2019.2905669

[28] Zhou, C., Zhang, Y., & Zhang, Y. (2021). Explainable AI for plant disease recognition: From black-box to interpretable models. Agricultural Systems, 190, 103120. https://doi.org/10.1016/j.agsy.2021.103120

[29] Dosovitskiy, A., Beyer, L., Kolesnikov, A., et al. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. International Conference on Learning Representations (ICLR).

[30] Kshetri, N. (2021). The role of digital technologies in agriculture: A review of research trends. Technological Forecasting and Social Change, 166, 120607.

[31] Lin, T., Wang, Y., Liu, X., & Qiu, X. (2022). A survey of transformers in vision: Foundations, advances, and applications. ACM Computing Surveys, 55(10), 1–41.

[32] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing