Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

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Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Prong 2 of Matter of Dhanasar (the petitioner is well positioned to advance the proposed endeavor) — the prong where past citation evidence is most probative. It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

207	212	4	2
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

98.0% independent of 51 classified citing papers

Citation type	Count
Independent	50
Self-citation	1
Co-author	0
Same-institution	0

156 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

Claim — Contribution 1

The researcher advanced smart agriculture by establishing a foundational framework for CNN applications, subsequently expanding this scope to multimodal data integration and novel remote sensing datasets.

The researcher's contribution centers on the systematic application of Convolutional Neural Networks (CNNs) to smart agriculture, anchored by the 2024 core paper 'Images and CNN applications in smart agriculture.' This work serves as the conceptual foundation for a broader research trajectory that addresses the evolving complexity of agricultural data analysis.

Originality in this line of work is suggested by the chronological progression from general CNN applications to more specialized domains. The 2025 follow-up, 'A review of CNN applications in smart agriculture using multimodal data,' indicates a shift toward integrating diverse data types, while 'AgriPotential' suggests the creation of new multi-spectral and multi-temporal remote sensing resources. This evolution implies a move from theoretical application to practical data infrastructure development.

The significance of this research is evidenced by substantial independent uptake. The core paper has accumulated 47 citations, while the multimodal review has garnered 166 citations, indicating rapid community engagement. With 98.0% of classified citations originating from independent researchers, the work demonstrates broad relevance and influence beyond the researcher's immediate circle, validating its impact on the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 51

CORE PAPER

Images and CNN applications in smart agriculture

2024 · European Journal of Remote Sensing 57 (1), 2352386, 2024 · 47 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Convolutional Neural Network Model for Flue Cured Tobacco Classification in Zimbabwe	Harare Institute of Technology	Zimbabwe	—
2	Agricultural robots and automated machinery for handling of nursery seedlings with special reference to the transplanting devices	ICAR-Central Institute of Agricultural Engineering	India	—
3	A convolutional neural network model and algorithm driven prototype for sustainable tilling and fertilizer optimization	Dublin High School	United States	—
4	Detection of diseases in cucumber using deep neural networks	Universidad Tecnológica de Bolívar	Colombia	—
5	Image classification-based system for disease diagnosis in coffee crops: A case study in the province of Rodriguez de Mendoza, northern Peru	Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas	Peru	—
6	Development of an AI-Enabled Vision-Based On-Site Rapid Detection of Nitrates and Nitrites from Drainage Samples	South Dakota State University	United States	—
7	A review of deep learning based agricultural remote sensing image segmentation	Jiangsu University	China	—
8	R-Based Graphical Representation of Trends in Food Production and Agriculture Value Chains in India	University of Bologna	Italy	—

No.	Citing paper	Citing institution(s)	Country	S2
9	Edge Integrated Vision Transformer Architecture with Cross Spectral Attention Fusion for Real Time Seed and Crop Health Diagnosis in Multimodal Precision ...	Sri Sairam Engineering College	India	—
10	Optimizing agricultural health using a compact convolutional transformer model for plant disease detection	Orebro Universitet, Princess Nourah bint Abdulrahman University, University of Haripur	Pakistan, Saudi Arabia, Sweden	—
11	Intellectual Property Rights in Smart Agriculture for Medicinal Plants	Career Point University, ICAR-Central Potato Research Institute	India	—
12	The Application of Artificial Intelligence and Deep Learning in Extracting Agricultural Parcel Boundaries and Its Role in Enhancing Spatial Data Infrastructure (SDI)	Shahid Beheshti University	Iran	—
13	YOLO Algorithm-Based Effective Orange Detection and Localization with Improved Data Augmentation	Cummins College of Engineering for Women, Smt. Kashibai Navale College of Engineering	India	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

FOLLOW-UP WORK

A review of CNN applications in smart agriculture using multimodal data

2025 · Sensors 25 (2), 472, 2025 · 166 citations (GS)

Field-normalised: 106 Semantic Scholar citations place it in the top 1% of Agricultural and Food Sciences papers from 2025 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Investigation of emerging technologies in agriculture: An in-depth look at smart farming, nano-agriculture, AI, and big data	Saveetha University	India	—
2	Remote Sensing and Artificial Intelligence in Flood Prediction: Progress, Challenges, and Prospects	Academy of Maritime Education and Training (AMET) Deemed to Be University, Karunya Institute of Technology and Sciences, Kongu Engineering College (Autonomous)	India	—
3	A paradigm-level evaluation of deep learning architectures for plant pest and disease recognition under data-scarce field conditions	Shandong Academy of Agricultural Sciences, Shandong University of Science and Technology	China	—
4	GroupCeptionNet: a lightweight model for classifying chili seed germination with macro images	Chonnam National University, Hulunbuir University	China, South Korea	—
5	A lightweight deep convolutional neural network development for soybean leaf disease recognition	Henan University of Science and Technology, Jiangsu University, Jilin University	China, Pakistan	—

No.	Citing paper	Citing institution(s)	Country	S2
6	A CNN-Based Deep Learning Architecture for Discriminating Botanical Adulteration and Complexities Among Commercial Apiaceae Medicinal Species	Iranian Biological Resource Center	Iran	—
7	Class-wise guided weighted soft voting for deep learning-based date palm nutrient deficiency classification	Moulay Ismail University of Meknès	Morocco	—
8	Sliding sampling and successive variational mode decomposition CNN-BiLSTM-attention based fault detection and early warning method for DC microgrid	State Grid Jiangsu Electric Power Co, Ltd	China	—
9	Chat Demeter: a multi-agent system for plant disease diagnosis integrating CNN-transformer models	Zhejiang A&F University	China	—
10	Concise Comparison of CNN Models On a Specified Dataset	Al-Imam Al-Adham University College, Al-Nahrain University, Al.nukhba University College	Iraq	—
11	AgriPINN: A Process-Informed Neural Network for Interpretable and Scalable Crop Biomass Prediction Under Water Stress	Leibniz Centre for Agricultural Landscape Research, Manchester Metropolitan University, University of Bonn	Germany, United Kingdom	—
12	Artificial Intelligence-Assisted Detection of Abiotic Stress in Agricultural Crops: Sensors, Computational Models, and Outlook	Mohanlal Sukhadia University	India	—
13	An Annotation-to-Detection Framework for Autonomous and Robust Vine Trunk Localization in the Field by Mobile Agricultural Robots	University of California, Riverside, Univ. of California, Riverside	United States	—
14	Image segmentation and machine learning modelling for water status determination and precision irrigation management	Abdul Wali Khan University Mardan, Linyi University, South Dakota State University	China, Pakistan, United States	—
15	YOLO-ELC: Enhanced Detection of Pavement Distresses Using UAV-Captured Images	Chinese Academy of Sciences, Hebei University of Technology	China	—
16	Machine Learning Algorithms and Their Effects on Crop Production in Agriculture: A Review	Gulf University, Kuwait University, Middle Technical University	Iraq, Kingdom of Bahrain, Kuwait	—
17	Toward Sustainable Farming: Artificial Intelligence Applications in the Detection and Management of Crop Diseases and Pests: A Systematic Review	Ibn Tofail University, Mohammed First University	Morocco	—
18	Machine Learning and Mathematical Modeling in Agricultural Development	Mother Teresa University, University "St. Kliment Ohridski" – Bitola	India, North Macedonia	—
19	AI-Driven Soil Texture Classification: Integrating Machine Learning, Deep Learning, and Multimodal Data Fusion for Precision Soil Conservation	Indian Institute of Technology Kharagpur	India	—
20	Transmission line icing prediction based on multi-source monitoring data	State Grid Shanxi Electric Power Research Institute	China	—

No.	Citing paper	Citing institution(s)	Country	S2
21	Machine Vision and Deep Learning for Smart Agriculture	CVR College of Engineering, Malla Reddy College of Engineering, Malla Reddy Engineering College	India	—
22	Technical Innovation in Farming 4.0 for the Future of Sustainable Agriculture	COER University, D.B.S.(PG) College, Forest Research Institute	India, Morocco	—
23	A New Transformer-Based Hybrid Model to Forecast Olive Fruit Fly Using Multimodal Data	Pablo de Olavide University	Spain	—
24	Machine Learning Applications in Modern Agriculture: Advancing Precision Farming Through Intelligent Systems	Kingston and St George's University, Sheffield Emergency Care Forum, University of Bath	United Kingdom	—
25	Applications of Language Models and Computer Vision for Natural Capital Accounting: Challenges and Opportunities in Achieving SDG 15	Universidad de Santiago de Chile, Universidad Santo Tomás	Chile	—
26	A Deep Learning Approach for Disease Detection in Maize Crops	Federal University of Technology, Akure	Nigeria	—
27	Digital Twins in Sustainable Agriculture in Precision Irrigation and Water Management: Challenges and Future Perspectives	Chitkara University, IIT Delhi, LUT University	Finland, India	—
28	Edge-Enabled Hybrid AI Framework for IoT-Based Crop Management and Irrigation Control	Koneru Lakshmaiah Education Foundation	India	—
29	Analisis Komparatif Arsitektur Deep Learning Untuk Aplikasi Computer Vision: Studi Literature Review	Universitas Nusa Mandiri	Indonesia	—
30	Plant Disease Detection Using Image Processing and Machine Learning	Vishwakarma Institute of Technology	India	—

Showing the 30 most-cited of 37 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

FOLLOW-UP WORK

AgriPotential: A Novel Multi-Spectral and Multi-Temporal Remote Sensing Dataset for Agricultural Potentials

2025 · 2025 International Conference on Content-Based Multimedia Indexing (CBMI), 1-6, 2025 · 2 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	SeDa: A Unified System for Dataset Discovery and Multi-Entity Augmented Semantic Exploration	East China University of Science and Technology	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Jiangsu University	China	SCImago #388 · THE 501–600	2
South Dakota State University	United States	SCImago #3569	2
Kohat University of Science & Technology	Pakistan	SCImago #7090 · THE 1201–1500	1
Shahid Beheshti University	Iran	SCImago #5942 · THE 801–1000 · QS 741-750	1
Indian Institute of Technology Kharagpur	India	SCImago #2152 · QS =215	1
Chitkara University	India	THE 601–800 · QS 1201-1400	1
Universitas Nusa Mandiri	Indonesia	—	1
Iranian Biological Resource Center	Iran	—	1
Toulouse INP	France	—	1
Academy of Maritime Education and Training (AMET) Deemed to Be University	India	—	1
Kongu Engineering College (Autonomous)	India	SCImago #9018	1
Sreenidhi Institute of Science and Technology	India	SCImago #10249	1
University of Wah	Pakistan	SCImago #7048	1
Hulunbuir University	China	—	1
Moulay Ismail University of Meknès	Morocco	—	1

Geographic distribution of citing authors

Country	Citing papers
India	15
China	10
Pakistan	5
United States	4
United Kingdom	3
Morocco	3
Indonesia	2
Colombia	2
Iraq	2
Iran	2
Saudi Arabia	1
South Korea	1

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Images and CNN applications in smart agriculture	51	Dhanasar — Prong 2 (well-positioned)