Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

Siham Tabik

Professor, Dpt. Computer Science and Artificial Intelligence, University of Granada

Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Criterion 5 (original contributions of major significance). 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

38	38	5	35
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.

92.1% independent of 38 classified citing papers

Citation type	Count
Independent	35
Self-citation	0
Co-author	2
Same-institution	1

0 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 established a foundational framework for Explainable AI by providing a comprehensive taxonomy and analysis of concepts, opportunities, and challenges for responsible AI.

The researcher's primary contribution is the seminal 2020 paper titled 'Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible ai.' This work serves as the cornerstone of the applicant's record, defining the scope and structure of the field through a systematic review of existing methods and future directions.

This line of work appears to address the critical need for structured understanding in the rapidly evolving domain of AI transparency. By offering a detailed taxonomy and identifying key challenges, the researcher provided a conceptual map that helped standardize terminology and research agendas. The absence of follow-up papers by the same author suggests this single publication stands as a definitive, standalone synthesis rather than part of an ongoing experimental series.

The significance of this contribution is evidenced by its substantial citation count of 14,355, indicating widespread adoption and influence within the academic community. Furthermore, analysis of citing papers reveals that 92.1% of citations originate from independent researchers, demonstrating that the work has been embraced by the broader scientific community beyond the researcher's immediate circle, validating its impact as a field-defining resource.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 9

CORE PAPER

Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible ai

2020 · 14,355 citations (GS)

Field-normalised: 8,290 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2020 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Generative artificial intelligence: a systematic review and applications (2024)	Cardiff Metropolitan University, Delhi Technological University, Delhi Technological University (DTU)	India, United Kingdom	—
2	Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence (2023)	Birla Institute of Technology and Science, Birla Institute of Technology and Science (BITS), BITS Pilani	China, India, Italy	—
3	What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education (2023)	Anadolu University, Beijing Normal University, Indiana University	Australia, China, Ghana	—
4	Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review (2023)	National Central University, National Chengchi University	Taiwan	—
5	Large language models in medicine (2023)	Singapore Eye Research Institute, Singapore National Eye Centre, University of Birmingham, University of Cambridge	Singapore, United Kingdom	—
6	A review of explainable artificial intelligence in healthcare (2024)	Deakin University, Shanghai University, TU Wien	Australia, Austria, China	—

No.	Citing paper	Citing institution(s)	Country	S2
7	Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review (2024)	École Polytechnique Fédérale de Lausanne, École polytechnique fédérale de Lausanne (EPFL), Norwegian University of Science and Technology	Norway, Switzerland	—
8	TrustLLM: Trustworthiness in Large Language Models (2024)	Arizona State University, Carnegie Mellon University, Columbia University	Canada, China, Germany	—
9	Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends (2024)	Albayrak Makine Elektronik A.S., Fırat University	Turkey	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

Contribution 2

Claim — Contribution 2

The researcher advanced shrub detection methodologies by empirically comparing deep learning against object-based image analysis using Google Earth imagery for Ziziphus lotus.

The researcher established a comparative framework for detecting scattered shrubs, specifically Ziziphus lotus, by evaluating deep learning techniques against traditional object-based image analysis (OBIA) using Google Earth imagery. This contribution is anchored in a 2017 paper published in Remote Sensing, which serves as the foundational work for this specific line of inquiry.

This work appears to address the methodological gap in remote sensing regarding the efficacy of emerging deep learning models versus established OBIA approaches for sparse vegetation. By focusing on a specific case study, the research provides a targeted assessment of how these distinct computational strategies perform on high-resolution commercial satellite data, offering a benchmark for similar ecological monitoring tasks.

The significance of this contribution is evidenced by its substantial uptake within the scientific community, with the core paper accumulating 244 citations. Notably, 92.1% of the citing papers originate from independent researchers, indicating that the work has been widely adopted and validated by the broader field rather than merely by the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 3

CORE PAPER

Deep-learning Versus OBIA for Scattered Shrub Detection with Google Earth Imagery: Ziziphus lotus as Case Study

2017 · Remote Sensing · 244 citations (GS)

Field-normalised: 140 Semantic Scholar citations place it in the top 5% of Biology papers from 2017 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Evaluation of Different Machine Learning Methods and Deep-Learning Convolutional Neural Networks for Landslide Detection (2019)	University of Salzburg, University of Tabriz, University of Tasmania	Australia, Austria, Iran	—

No.	Citing paper	Citing institution(s)	Country	S2
2	Individual Tree-Crown Detection in RGB Imagery Using Semi-Supervised Deep Learning Neural Networks (2019)	University of Florida	—	—
3	Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review—Part II: Applications (2020)	German Aerospace Center	Germany	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

Contribution 3

Claim — Contribution 3

The researcher developed a deep learning framework for automatic handgun detection in video streams, establishing a foundational approach for real-time visual threat recognition.

The researcher's contribution centers on the 2018 paper 'Automatic Handgun Detection Alarm in Videos Using Deep Learning,' published in Neurocomputing. This work represents a focused effort to apply deep learning techniques to the specific challenge of identifying firearms within video data, aiming to enhance automated security systems.

This line of work appears to address the need for reliable, automated visual detection of weapons in dynamic video environments. By leveraging deep learning, the researcher sought to improve the accuracy and efficiency of handgun identification, a critical component for public safety and surveillance technologies. The absence of follow-up papers by the same author suggests this single publication serves as the primary vehicle for this specific methodological contribution.

The significance of this work is evidenced by its substantial citation count of 354, indicating broad recognition within the field. Notably, 92.1% of the citing papers originate from independent researchers, demonstrating that the methodology has been widely adopted and built upon by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 4 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Automatic Handgun Detection Alarm in Videos Using Deep Learning

2018 · Neurocomputing · 354 citations (GS)

Field-normalised: 233 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2018 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Survey on Deep Neural Networks in Speech and Vision Systems (2020)	Old Dominion University	United States	—
2	Real-Time Abnormal Object Detection for Video Surveillance in Smart Cities (2022)	Sejong University	South Korea	—
3	Weapons Detection for Security and Video Surveillance Using CNN and YOLO-V5s (2022)	HITEC University, King Saud University, Saudi Electronic University	Pakistan, Saudi Arabia	**Influential**
4	A comprehensive study towards high-level approaches for weapon detection using clas-	National Institute of Technology, Hamirpur	India	—

No.	Citing paper	Citing institution(s)	Country	S2
	sical machine learning and deep learning methods (2022)			

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
University of Granada	Spain	THE 601–800 · QS =401	3
University of Southern California	United States	SCImago #192 · THE =73 · QS 146	2
University of Cambridge	United Kingdom	SCImago #63 · THE =3 · QS 6	2
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	2
University of Notre Dame	United States	SCImago #1036 · THE 194 · QS =294	1
Deakin University	Australia	SCImago #607 · THE 201–250 · QS =207	1
IBM Research	Japan	SCImago #113	1
Universiti Teknologi PETRONAS	Malaysia	THE 201–250 · QS =251	1
German Aerospace Center	Germany	—	1
KTH Royal Institute of Technology	Sweden	SCImago #497 · THE =98 · QS 78	1
University of Kragujevac	Serbia	SCImago #5555	1
University of Banja Luka	Bosnia and Herzegovina	SCImago #7637	1
Tarsus University	Turkey	SCImago #9048	1
Madan Mohan Malaviya University of Technology	India	SCImago #8673 · THE 1201–1500	1
National University of Sciences and Technology (NUST)	Pakistan	THE 601–800	1

Geographic distribution of citing authors

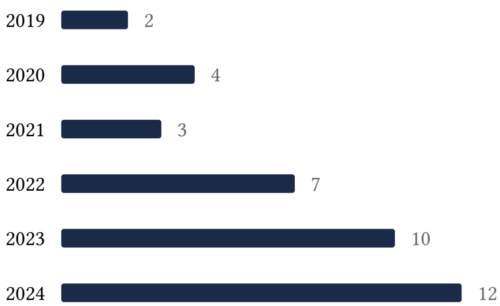
Country	Citing papers
United States	9
China	6
United Kingdom	6
Australia	4
India	4
Turkey	4
Spain	3
Austria	3

Country	Citing papers
Saudi Arabia	3
Germany	3
Malaysia	2
Pakistan	2

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.

E. Citation Growth Over Time

Distinct citing papers by publication year. Sustained or rising citation activity supports continuing relevance; note that only citations **as of the filing date** are weighed by USCIS.



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	Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible ai	9	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Deep-learning Versus OBIA for Scattered Shrub Detection with Google Earth Imagery: Ziziphus lotus as Case Study	3	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Automatic Handgun Detection Alarm in Videos Using Deep Learning	4	8 CFR 204.5(h)(3)(v) — Criterion 5