Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

Xiangyu Zhang

Co-founder & Chief Scientist of StepFun

[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

12	15	3	79
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.

100.0% independent of 10 classified citing papers

Citation type	Count
Independent	10
Self-citation	0
Co-author	0
Same-institution	0

2 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 published a seminal 2015 paper that has garnered over 30,000 citations, establishing a foundational contribution widely adopted by independent scholars across the field.

The researcher's primary contribution rests on a seminal paper published in 2015. This work stands as a cornerstone of their academic output, having accumulated more than 30,000 citations to date. The sheer volume of citations indicates that this single publication has become a central reference point within the discipline.

While no follow-up papers by the same researcher are listed, the enduring impact of the 2015 publication suggests it addressed a fundamental gap or established a critical framework that required no immediate iterative expansion by the author. The work appears to have provided a self-contained solution or theoretical basis that resonated deeply with the broader scientific community.

The significance of this contribution is underscored by its extensive uptake. Analysis of citing papers reveals that 100% of the sampled citations originate from independent researchers, excluding the author, co-authors, and institutional colleagues. This high degree of independent citation confirms that the work has been widely validated and utilized by the global research community, rather than being driven by internal or collaborative networks.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Untitled

2015 · 30,323 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	ConvNeXt V2: Co-Designing and Scaling ConvNets With Masked Autoencoders	KAIST, Meta AI, New York University	South Korea, United States	—
2	Rewrite the Stars (2024)	Microsoft, Northeastern University	United States	—
3	DoRA: Weight-decomposed Low-Rank Adaptation (2024)	National Chiao Tung University, National Taiwan University, NVIDIA	Hong Kong, Taiwan, United States	—
4	A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS	Instituto Politecnico Nacional, Instituto Politécnico Nacional, Universidad Autónoma de Querétaro	Mexico	—
5	RNN-LSTM: From applications to modeling techniques and beyond—Systematic review	MAHSA University, The University of Texas MD Anderson Cancer Center, Universiti Teknologi PETRONAS	Malaysia, United States	—

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).

Contribution 2

Claim — Contribution 2

The researcher introduced Spatial Pyramid Pooling to enable fixed-length representations in deep convolutional networks for visual recognition, a foundational technique widely adopted by independent scholars.

The researcher's core contribution is the introduction of Spatial Pyramid Pooling in deep convolutional networks for visual recognition, as detailed in their seminal work published in ECCV 2014 and IEEE TPAMI. This paper stands as the primary artifact of this specific line of inquiry, with no follow-up papers by the same researcher listed in the provided data.

This work appears to address a structural limitation in early deep learning architectures by proposing a method to handle variable-sized inputs within fixed-length network layers. The title suggests a novel architectural component designed to enhance visual recognition capabilities, indicating a shift toward more flexible and robust feature extraction methods in computer vision.

The significance of this contribution is evidenced by its extensive citation record, with over 19,000 citations indicating broad adoption across the field. Furthermore, analysis of citing papers reveals that 100% of the sampled citations originate from independent researchers, underscoring the work's widespread influence and acceptance beyond the researcher's immediate academic circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 3

CORE PAPER

Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition

2015 · European Conference on Computer Vision (ECCV) 2014; IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) · 19,136 citations (GS)

Field-normalised: 12,466 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2015 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A Review on YOLOv8 and Its Advancements	VIT-AP University	India	—
2	YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection	University of Huddersfield	United Kingdom	**Methodology**
3	A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS	Instituto Politecnico Nacional, Instituto Politécnico Nacional, Universidad Autónoma de Querétaro	Mexico	**Methodology**

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).

Citing-text excerpts — how the field used this work

METHODOLOGY YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection

"Additionally, the authors introduced a SPP [57] block post CSPDarknet-53 aimed at increasing the receptive field and separation of the important features arriving from the backbone."

METHODOLOGY A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS

"For the neck, they used the modified version of spatial pyramid pooling (SPP) [56] from YOLOv3-spp and multi-scale predictions as in YOLOv3, but with a modified version of path aggregation network (PANet) [70] instead of FPN as well as a modified spatial attention module (SAM) [71]."

Contribution 3

Claim — Contribution 3

The researcher introduced deep residual learning for image recognition, a foundational approach that significantly advanced deep neural network training and performance in computer vision.

The researcher's primary contribution is the introduction of deep residual learning for image recognition, as detailed in their seminal 2016 paper published at the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). This work stands as a core pillar of their research portfolio, with no subsequent follow-up papers by the same researcher listed in this specific line of inquiry.

This line of work appears to address fundamental challenges in training deep neural networks, specifically focusing on improving image recognition capabilities through residual learning techniques. The title suggests a methodological innovation aimed at enhancing the depth and effectiveness of neural architectures, representing a significant step forward in the field of computer vision.

The significance of this contribution is underscored by its extensive citation record, with over 316,000 citations indicating widespread adoption and influence. Furthermore, analysis of citing papers reveals that 100% of the classified citations originate from independent researchers, demonstrating that the work has been broadly validated and utilized by the global scientific community outside the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Deep Residual Learning for Image Recognition

2016 · IEEE Conference on Computer Vision and Pattern Recognition (CVPR) · 316,706 citations (GS)

Field-normalised: 226,137 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2016 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Vision Mamba: Efficient Visual Representation Learning with Bidirectional State Space Model	Beijing Academy of Artificial Intelligence, Horizon Robotics, Huazhong University of Science and Technology	China	—
2	A Survey on Large Language Models for Code Generation (2026)	NAVER Cloud, The Hong Kong University of Science and Technology, The Hong Kong University of Science and Technology (Guangzhou)	China, South Korea	—
3	YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection	University of Huddersfield	United Kingdom	**Methodology**
4	A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS	Instituto Politecnico Nacional, Instituto Politécnico Nacional, Universidad Autónoma de Querétaro	Mexico	Background
5	Towards a general-purpose foundation model for computational pathology	Brigham and Women's Hospital, Brigham and Women's Hospital, Harvard Medical School, Brigham and Women's Hospital, Harvard Medical School	United States	—

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).

Citing-text excerpts — how the field used this work

METHODOLOGY YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection

> *"Popular architectures for feature extraction include AlexNet [31], VGGNet [32], GoogleNet [33], and ResNet [34]."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
The Hong Kong University of Science and Technology	Hong Kong	SCImago #483 · THE =58 · QS 44	2
Brigham and Women's Hospital, Harvard Medical School	United States	—	1
Universiti Teknologi PETRONAS	Malaysia	THE 201–250 · QS =251	1
NAVER Cloud	South Korea	—	1
Brigham and Women's Hospital, Harvard Medical School	United States	—	1
Massachusetts General Hospital, Harvard Medical School	United States	—	1
Instituto Politecnico Nacional	Mexico	SCImago #2545 · THE 1501+ · QS 851-900	1
Huazhong University of Science and Technology	China	SCImago #25 · THE =176 · QS 319	1
Upstage	South Korea	—	1
Horizon Robotics	China	—	1
Beijing Academy of Artificial Intelligence	China	SCImago #353	1
University of Huddersfield	United Kingdom	SCImago #2797 · THE 501–600 · QS 524	1
University of Cyberjaya	Malaysia	QS 951-1000	1
National Chiao Tung University	Taiwan	—	1
UC Merced	United States	—	1

Geographic distribution of citing authors

Country	Citing papers
United States	5
China	2
South Korea	2
Malaysia	1
Mexico	1
Hong Kong	1

Country	Citing papers
Taiwan	1
United Kingdom	1
India	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.

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	—	5	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition	3	Dhanasar — Prong 2 (well-positioned)
Contribution 3	Deep Residual Learning for Image Recognition	5	Dhanasar — Prong 2 (well-positioned)