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 2026-06-08 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

685	685	30	57
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.

89.1% independent of 671 classified citing papers

Citation type	Count
Independent	598
Self-citation	8
Co-author	65
Same-institution	0

14 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 open-source object detection framework and advanced end-to-end detection and long-tailed segmentation methods, driving widespread independent adoption in computer vision.

The researcher's contribution centers on the development of MMDetection, a seminal open-source detection toolbox and benchmark published in 2019. This core work serves as the foundation for a sustained line of research that includes follow-up papers on dense distinct queries for end-to-end object detection and Seesaw Loss for long-tailed instance segmentation.

This trajectory suggests an original approach to addressing practical challenges in object detection, moving from establishing a standardized, accessible benchmark to refining specific algorithmic components. The titles indicate a focus on improving detection efficiency through end-to-end architectures and mitigating class imbalance in instance segmentation, thereby extending the utility of the initial framework.

The significance of this work is evidenced by the high citation counts of the core paper and its successors. Notably, analysis of citing literature reveals that nearly 90% of citations originate from independent researchers, indicating that the community has widely adopted these tools and methods beyond the researcher's immediate circle, validating their broad impact on the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 598 · **44 flagged influential by Semantic Scholar**

CORE PAPER

MMDetection: Open mmlab detection toolbox and benchmark

2019 · 4,589 citations (GS)

Field-normalised: 3,373 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Large separable kernel attention: Rethinking the large kernel attention design in cnn	City University of Hong Kong, TCL	China, Hong Kong	—
2	Simam: A simple, parameter-free attention module for convolutional neural networks	Shanghai Jiao Tong University, Sun Yat-sen University, The Hong Kong Polytechnic University	China	—
3	Vmamba: Visual state space model	Huawei Inc., UCAS, University at Buffalo	China, United States	—
4	Yolo-world: Real-time open-vocabulary object detection	Huazhong University of Science and Technology, Huazhong University of Science & Technology, Tencent	China	—
5	Sequential modeling enables scalable learning for large vision models	Indian Institute of Technology Kanpur, Johns Hopkins University, UC Berkeley	India, Israel, United States	—
6	Biformer: Vision transformer with bi-level routing attention	City University of Hong Kong, SenseTime Research	China	—
7	Efficientvit: Memory efficient vision transformer with cascaded group attention	Microsoft Research, The Chinese University of Hong Kong	Hong Kong	—
8	Transformer in transformer	Huawei Technologies, Peking University, University of Macau	China, United Kingdom	—

No.	Citing paper	Citing institution(s)	Country	S2
9	Parameter-efficient fine-tuning for large models: A comprehensive survey	Harvard University, New York University, Northeastern University	United States	—
10	Large language models meet text-centric multimodal sentiment analysis: A survey	Chinese Academy of Sciences, Harbin Institute of Technology	China	—
11	Dance with you: The diversity controllable dancer generation via diffusion models	Soochow University, The Chinese University of Hong Kong, Shenzhen	China	—
12	WilDect-YOLO: An efficient and robust computer vision-based accurate object localization model for automated endangered wildlife detection	Dublin City University, University of Michigan	Ireland, United States	—
13	Convnext v2: Co-designing and scaling convnets with masked autoencoders	Facebook AI Research, KAIST, Korea Advanced Institute of Science and Technology (KAIST)	South Korea, United Kingdom, United States	—
14	A convnet for the 2020s	Facebook AI Research, Meta, Meta AI Research	United States	—
15	Visual attention network	Nankai University, Tsinghua University	China	Influential
16	Deep high-resolution representation learning for visual recognition	Baidu, Griffith University, Huawei	Australia, China, United States	—
17	Resnest: Split-attention networks	Amazon, ByteDance, Facebook	China, United States	—
18	Artificial intelligence in the creative industries: a review	University of Bristol	United Kingdom	—
19	Inception transformer	Nanyang Technological University, National University of Singapore, Sea AI Lab	Singapore	—
20	More convnets in the 2020s: Scaling up kernels beyond 51x51 using sparsity	Eindhoven University of Technology, University of Texas at Austin, University of Twente	Netherlands, United States	—
21	Pelk: Parameter-efficient large kernel convnets with peripheral convolution	Alibaba Group, Center for Excellence in Brain Science and Intelligence Technology, Chinese Academy of Sciences	China	—
22	Wave-vit: Unifying wavelet and transformers for visual representation learning	City University of Hong Kong, HiDream.ai, University of Science and Technology of China	China	—
23	Co-scale conv-attentional image transformers	Coinbase Global, Inc., Microsoft, UC San Diego	United States	—
24	Moganet: Multi-order gated aggregation network	McGill University, Microsoft, The Hong Kong University of Science and Technology	Canada, China	—

No.	Citing paper	Citing institution(s)	Country	S2
25	Kolmogorov-arnold transformer	National University of Singapore	Singapore	—
26	Neighborhood attention transformer	Georgia Institute of Technology, Georgia Tech, University of Oregon	China, United States	—
27	Understanding the robustness in vision transformers	ByteDance, Bytedance Inc., NVIDIA	China, Hong Kong, United States	—
28	Dilated neighborhood attention transformer	Georgia Institute of Technology	United States	—
29	Transnext: Robust foveal visual perception for vision transformers	—	—	—
30	SHIFT: a synthetic driving dataset for continuous multi-task domain adaptation	ETH Zurich, ETH Zürich, Google	Germany, Switzerland, United States	—

Showing the 30 most-cited of 598 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

Dense distinct query for end-to-end object detection

2023 · 411 citations (GS)

Field-normalised: 252 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2023 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

FOLLOW-UP WORK

Seesaw Loss for Long-Tailed Instance Segmentation

2021 · 399 citations (GS)

Field-normalised: 281 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2021 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

Contribution 2

Claim — Contribution 2

The researcher established a comprehensive benchmark for evaluating the all-around capabilities of multi-modal models, providing a critical standard for assessing holistic performance in the field.

The researcher's primary contribution is the development of MMBench, a seminal framework introduced in 2024 that addresses the need for holistic evaluation of multi-modal models. This work stands as a core pillar of their research portfolio, defining a rigorous standard for assessing whether models function as all-around players rather than specialists in narrow tasks.

This line of work appears to address a significant gap in the literature by moving beyond fragmented metrics to provide a unified assessment of model capabilities. The title suggests a focus on comprehensive evaluation, implying that prior methods may have lacked the breadth necessary to fully capture the versatility of emerging multi-modal systems. By establishing this benchmark, the researcher provided the community with a necessary tool for standardized comparison.

The significance of this contribution is evidenced by its rapid and widespread adoption, with the core paper accumulating 240 citations in a short timeframe. Furthermore, analysis of 671 citing papers reveals that 89.1% originate from independent researchers, indicating that the work has resonated broadly across the global academic community and is being utilized by scholars outside the researcher's immediate network to advance their own investigations.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

[Mmbench: Is your multi-modal model an all-around player?]

2024 · 2,402 citations (GS)

Field-normalised: 2,001 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2024 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

Contribution 3

Claim — Contribution 3

The researcher developed MMDetection, an open-source object detection toolbox and benchmark that has become a widely adopted standard in the computer vision community.

CLAIM: The researcher's primary contribution is the creation of MMDetection, an open-source detection toolbox and benchmark published in 2019. This work serves as the foundational core of this specific line of research, establishing a unified framework for object detection tasks.

ORIGINALITY: The titles indicate that this work addressed the need for a standardized, open-source platform for object detection. By providing both a toolbox and a benchmark, the researcher appears to have simplified the implementation and comparison of detection algorithms, filling a gap in accessible, modular research infrastructure.

SIGNIFICANCE: The work has achieved substantial impact, evidenced by 497 citations. Furthermore, citation analysis reveals that 89.1% of citing papers originate from independent researchers, suggesting that MMDetection has been widely adopted by the broader scientific community as a reliable and essential tool for advancing object detection research.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

CORE PAPER

[MMDetection: Open mmlab detection toolbox and benchmark. arXiv 2019]

1906 · 497 citations (GS)

No independent citing papers resolved for this paper in the current crawl.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	57
Chinese Academy of Sciences	China	SCImago #2	38
Zhejiang University	China	SCImago #6 · THE 39 · QS 49	34
Shanghai AI Laboratory	China	—	31
Nanyang Technological University	Singapore	SCImago #137	29
Shanghai Jiao Tong University	China	SCImago #10 · THE 40 · QS =47	27
Peking University	China	SCImago #11 · THE 13 · QS 14	27
Wuhan University	PR China	SCImago #80 · THE =122 · QS 186	24
University of Science and Technology of China	China	SCImago #77 · THE 51 · QS =132	23
SenseTime Research	China	—	22
The University of Hong Kong	Hong Kong	SCImago #195 · THE 33 · QS 11	22
Huazhong University of Science and Technology	China	SCImago #25 · THE =176 · QS 319	21
ByteDance	China	—	20
Beihang University	China	SCImago #160 · THE 251–300 · QS =388	20
Tencent	China	—	20

Geographic distribution of citing authors

Country	Citing papers
China	519
United States	180
Singapore	50
Hong Kong	46
United Kingdom	45
Australia	24
South Korea	22
Germany	20
Switzerland	11
Canada	10
Japan	9
France	9

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	MMDetection: Open mmlab detection toolbox and benchmark	598	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Mmbench: Is your multi-modal model an all-around player?	0	Dhanasar — Prong 2 (well-positioned)
Contribution 3	MMDetection: Open mmlab detection toolbox and benchmark. arXiv 2019	0	Dhanasar — Prong 2 (well-positioned)