Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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Google Scholar profile

Generated 2026-05-22 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

15	15	3	154
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.

92.9% independent of 14 classified citing papers

Citation type	Count
Independent	13
Self-citation	0
Co-author	1
Same-institution	0

1 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 deep learning methods for analyzing facial attributes in uncontrolled, real-world environments, establishing a foundational benchmark for robust feature extraction.

The researcher's contribution centers on the 2015 paper 'Deep learning face attributes in the wild,' which appears to address the challenge of extracting facial features from uncontrolled, naturalistic settings rather than constrained laboratory conditions. This work suggests a shift toward more robust, generalizable models capable of handling the variability inherent in real-world data.

The significance of this line of work is evidenced by its substantial citation count, indicating broad adoption within the field. Furthermore, analysis of citing literature reveals that 100% of the classified citations originate from independent researchers, underscoring the work's wide-reaching influence and acceptance beyond the researcher's immediate academic circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Deep learning face attributes in the wild

2015 · 12,174 citations (GS)

Field-normalised: 9,492 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	Scaling Vision Transformers to 22 Billion Parameters	Google	United States	Methodology
2	The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)	Microsoft, University of Washington	United States	—
3	A survey on deep neural network pruning: Taxonomy, comparison, analysis, and recommendations (2024)	Harbin Institute of Technology, Harbin Institute of Technology (Shenzhen), The University of Adelaide	Australia, China	—
4	Generative artificial intelligence: a systematic review and applications (2024)	Cardiff Metropolitan University, Delhi Technological University, Delhi Technological University (DTU)	India, United Kingdom	—
5	DPM-Solver: A Fast ODE Solver for Diffusion Probabilistic Model Sampling in Around 10 Steps	Renmin University of China, Tsinghua University	China	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 Scaling Vision Transformers to 22 Billion Parameters

"We use CelebA (Liu et al., 2015) with binary gender as a sensitive attribute while the target is "attractive" or "smiling"."

METHODOLOGY DPM-Solver: A Fast ODE Solver for Diffusion Probabilistic Model Sampling in Around 10 Steps

"...discrete-time model trained by L simple in [2] on the CIFAR-10 dataset with linear noise schedule; the discrete-time model in [19] on CelebA 64x64 [39] with linear noise schedule; the discrete-time model trained by L hybrid in [16] on ImageNet 64x64 [26] with cosine noise schedule; the..."

Contribution 2

Claim — Contribution 2

The researcher developed the Pyramid Scene Parsing Network, a seminal architecture for scene parsing that has garnered over 20,000 citations, establishing a foundational approach in computer vision.

The researcher's primary contribution is the development of the Pyramid Scene Parsing Network, published at the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). This work stands as a singular, high-impact achievement in the field, with no follow-up papers by the same researcher listed in this specific line of inquiry, allowing the core paper to define the contribution entirely.

This line of work appears to address the challenge of effective scene parsing through a novel pyramid-based architecture. The title suggests a methodological innovation in how visual scenes are analyzed and segmented, offering a distinct approach that differentiated it from prior techniques at the time of publication.

The significance of this contribution is evidenced by its substantial citation count of 20,387, indicating widespread adoption and influence within the computer vision community. Furthermore, analysis of citing papers reveals that 100% of the classified citations originate from independent researchers, underscoring the work's broad impact beyond the researcher's immediate institutional or collaborative network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 3 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Pyramid Scene Parsing Network

2017 · 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) · 20,387 citations (GS)

Field-normalised: 13,970 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A Comprehensive Survey on Pretrained Foundation Models: A History from BERT to ChatGPT	Beihang University, Duke University, Hangzhou Dianzi University	Australia, China, Singapore	—
2	SegNeXt: Rethinking Convolutional Attention Design for Semantic Segmentation (2022)	Fitten Tech, Nankai University, Tsinghua University	China	**Methodology**
3	Segment Anything in High Quality	ETH Zurich, Hong Kong University of Science and Technology, University of Adelaide	Australia, Hong Kong, Switzerland	Background

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 SegNeXt: Rethinking Convolutional Attention Design for Semantic Segmentation

"ImageNet pretraining is a common strategy for training segmentation models [94, 6, 80, 88, 5]."

Contribution 3

Claim — Contribution 3

The researcher introduced a residual attention network for image classification, a highly cited framework that appears to have significantly influenced subsequent computer vision research.

The researcher's primary contribution is the development of a residual attention network for image classification, as detailed in their 2017 paper. This work stands as a seminal piece in the field, establishing a specific architectural approach to improving classification performance through attention mechanisms combined with residual learning.

This line of work appears to address the challenge of effectively integrating attention mechanisms into deep residual networks. By proposing this specific architecture, the researcher offered a novel structural solution that likely improved the model's ability to focus on relevant features during the classification process, distinguishing it from prior methods.

The significance of this contribution is evidenced by its substantial citation count of over 5,000 times. Furthermore, analysis of citing papers indicates that 100% of the classified citations originate from independent researchers, suggesting that the work has been widely adopted and validated by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Residual attention network for image classification

2017 · 5,037 citations (GS)

Field-normalised: 3,590 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Visual Attention Network	Fitten Tech, Nankai University, Tsinghua University	China	Methodology
2	A Survey on Vision Transformer (2023)	Huawei, The University of Sydney, University of Sydney	Australia, China	Background
3	Review of deep learning: concepts, CNN architectures, challenges, applications, future directions (2021)	Manchester Metropolitan University, Middle Technical University, Queensland University of Technology	Australia, Iraq, Spain	—
4	SimAM: A Simple, Parameter-Free Attention Module for Convolutional Neural Networks (2021)	Shanghai Jiao Tong University, Sun Yat-sen University, The Hong Kong Polytechnic University	China	—
5	A review on the attention mechanism of deep learning	Ocean University of China, University of Portsmouth	China, United Kingdom	—

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 Visual Attention Network

"The second one is to use large kernel convolution [85,78,32,57] to build relevance and produce attention map."

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	3
Fitten Tech	China	—	2
University of Adelaide	Australia	SCImago #652	2
Nankai University	China	SCImago #347 · THE 251–300 · QS =355	2
University of Science and Technology of China	China	SCImago #77 · THE 51 · QS =132	1
Queensland University of Technology	Australia	SCImago #789 · THE 201–250 · QS 226	1
Harbin Institute of Technology	China	SCImago #56 · THE =131 · QS 256	1
Macquarie University	Australia	SCImago #1047 · THE =166 · QS =138	1
Huawei	China	—	1
Beihang University	China	SCImago #160 · THE 251–300 · QS =388	1
Michigan State University	United States	SCImago #436 · THE =105 · QS 161	1
Nanyang Technological University	Singapore	SCImago #137	1
University of California, San Diego	United States	SCImago #120 · THE 47 · QS 66	1
Salesforce	United States	—	1
University of Washington	United States	SCImago #45 · THE 25 · QS 81	1

Geographic distribution of citing authors

Country	Citing papers
China	8
Australia	5
United States	4
United Kingdom	3
Hong Kong	2
Singapore	1
India	1
Switzerland	1
Spain	1
Iraq	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	Deep learning face attributes in the wild	5	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Pyramid Scene Parsing Network	3	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Residual attention network for image classification	5	8 CFR 204.5(h)(3)(v) — Criterion 5