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 2026-05-21 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

10	10	5	5
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

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 developed a machine learning framework for detecting depression using structural and functional MRI data, establishing a foundational approach in neuroimaging-based mental health diagnostics.

CLAIM: The researcher's primary contribution is the development of a machine learning approach for depression detection utilizing both structural (sMRI) and resting-state functional (rs-fMRI) magnetic resonance imaging data, as detailed in their 2021 publication. This work serves as the cornerstone of their research line in computational psychiatry.

ORIGINALITY: The titles indicate a focus on integrating multimodal neuroimaging data to improve diagnostic accuracy for depression. By combining structural and functional metrics within a machine learning pipeline, this line of work appears to address the challenge of identifying robust biomarkers for mental health conditions, moving beyond single-modality analyses.

SIGNIFICANCE: The core paper has accumulated 60 citations, suggesting it has become a recognized reference in the field. Notably, 100% of the classified citing papers originate from independent researchers, indicating that the work has influenced the broader scientific community beyond the researcher's immediate institution or collaboration network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1

CORE PAPER

Depression detection from sMRI and rs-fMRI images using machine learning

2021 · 60 citations (GS)

Field-normalised: 40 Semantic Scholar citations place it in the top 10% of Medicine papers from 2021 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	The diagnostic performance of machine learning based on resting-state functional magnetic resonance imaging data for major depressive disorders: a systematic review and meta-analysis. (2023)	Second Xiangya Hospital, Central South University	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).

Contribution 2

Claim — Contribution 2

The researcher developed methods for feature selection and imbalanced data handling to improve depression detection accuracy in clinical settings.

The researcher's contribution centers on the 2018 paper titled 'Feature selection and imbalanced data handling for depression detection.' This work addresses the technical challenges of identifying depression through computational means, specifically focusing on optimizing data features and managing class imbalance, which are critical hurdles in medical diagnostic modeling.

This line of work appears to address the gap in reliable automated depression detection systems by tackling two persistent issues: selecting the most relevant clinical or behavioral features and handling the skewed distribution of positive versus negative cases. By integrating these two aspects, the research suggests a more robust approach to building predictive models that are less prone to bias and overfitting.

The significance of this contribution is evidenced by its uptake in the broader scientific community. With 11 citations, all originating from independent researchers outside the author's immediate circle, the work demonstrates genuine external validation. This high degree of independent citation indicates that the methodology has been recognized as a useful reference point by other scholars working in related fields.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 2

CORE PAPER

Feature selection and imbalanced data handling for depression detection

2018 · 11 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Machine learning-based predictive modeling of depression in hypertensive populations. (2022)	Seoul National University, University of Washington Bothell	South Korea, United States	—
2	Finding the best predictive model for hypertensive depression in older adults based on machine learning and metabolomics research. (2024)	Shanghai University of Medicine and Health Sciences Affiliated Zhoupu Hospital, Shanghai YangZhi Rehabilitation Hospital, Tongji University	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).

Contribution 3

Claim — Contribution 3

The researcher developed a deep learning framework for depression detection using feature extraction from sMRI images, establishing a methodological approach for neuroimaging-based mental health diagnostics.

The researcher's contribution centers on the 2019 paper titled 'Depression detection using feature extraction and deep learning from sMRI images.' This work represents a focused effort to apply advanced computational techniques to structural magnetic resonance imaging data for the purpose of identifying depression. The titles indicate a methodological innovation that combines feature extraction with deep learning architectures to analyze brain scans.

This line of work appears to address the challenge of automating or enhancing the diagnostic process for depression through neuroimaging. By integrating deep learning with sMRI analysis, the researcher likely sought to uncover subtle patterns in brain structure that correlate with depressive disorders. The absence of follow-up papers in the provided data suggests this core publication stands as the primary articulation of this specific technical approach.

The significance of this contribution is evidenced by its citation record. With 17 citations, the work has attracted attention from the broader scientific community. Notably, 100% of the classified citing papers originate from independent researchers, indicating that the methodology or findings have been recognized and utilized by scholars outside the researcher's immediate institution or collaboration network. This independent uptake suggests the work has provided a useful reference point for others exploring similar intersections of AI and psychiatry.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1

CORE PAPER

Depression detection using feature extraction and deep learning from sMRI images

2019 · 17 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	[A Two-Stage Model for Predicting Mild Cognitive Impairment to Alzheimer's Disease Conversion.](#) (2022)	Guangdong Provincial People's Hospital, Jingmen No. 2 People's Hospital, Qingdao University	China	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).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Yantai Yuhuangding Hospital	China	SCImago #8096	2
Shandong Technology and Business University	China	SCImago #7214	2
Universiti Tenaga Nasional	Malaysia	THE 601–800 · QS =551	1
South China University of Technology	China	SCImago #111 · THE 251–300 · QS 377	1
Qingdao University	China	SCImago #489 · THE 601–800	1
Universiti Putra Malaysia	Malaysia	THE 501–600 · QS =134	1
University of Washington Bothell	United States	—	1
Jingmen No. 2 People's Hospital	China	—	1
Qingdao Hospital, University of Health and Rehabilitation Sciences (Qingdao Municipal Hospital)	China	—	1
The Affiliated Hospital of Qingdao University	China	SCImago #3281	1
Kyungnam University	South Korea	SCImago #8678	1
Shanghai University of Medicine and Health Sciences Affiliated Zhoupu Hospital	China	—	1
Shanghai YangZhi Rehabilitation Hospital, Tongji University	China	—	1
Second Xiangya Hospital, Central South University	China	—	1
Seoul National University	South Korea	SCImago #135 · THE =58 · QS =38	1

Geographic distribution of citing authors

Country	Citing papers
China	6
South Korea	2
Malaysia	1

Country	Citing papers
South Africa	1
United States	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	Depression detection from sMRI and rs-fMRI images using machine learning	1	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Feature selection and imbalanced data handling for depression detection	2	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Depression detection using feature extraction and deep learning from sMRI images	1	8 CFR 204.5(h)(3)(v) — Criterion 5