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

16	16	4	4
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 16 classified citing papers

Citation type	Count
Independent	16
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 deep learning framework utilizing binary patterns to enhance face recognition accuracy, as demonstrated in their 2018 ICCIDS publication.

The researcher's contribution centers on the integration of deep learning techniques with binary pattern analysis for face recognition. This work is anchored by the 2018 paper 'Deep learning on binary patterns for face recognition,' published in Procedia Computer Science following its presentation at ICCIDS 2018. The titles indicate a focus on leveraging binary representations within neural network architectures to improve identification performance.

This line of work appears to address the computational and representational challenges inherent in traditional face recognition systems. By combining deep learning with binary patterns, the researcher likely sought to create a more efficient or robust method for feature extraction and matching. The absence of follow-up papers by the same author suggests this specific contribution stands as a distinct, self-contained advancement in the field.

The significance of this work is evidenced by its citation record. With 25 citations, the paper has attracted attention from the broader academic community. Notably, 100% of the classified citing papers originate from independent researchers, indicating that the methodology or findings have been adopted and built upon by scholars outside the researcher's immediate institution or collaboration network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5 · **2 flagged influential by Semantic Scholar**

CORE PAPER

Deep learning on binary patterns for face recognition

2018 · International Conference on Computational Intelligence and Data Science (ICCIDS 2018), published in Procedia Computer Science, Volume 132, pages 76-83 · 25 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A Study on various state of the art of the Art Face Recognition System using Deep Learning Techniques (2019)	—	—	Background
2	Automatic generation of building information models from digitized plans (2020)	Northumbria University	United Kingdom	—
3	Improved local descriptor (ILD): a novel fusion method in face recognition. (2023)	Graphic Era Deemed to be University	India	Influential
4	Effective Face Recognition using Adaptive Multi-scale Transformer-based Resnet with Optimal Pattern Extraction (2023)	—	—	Methodology
5	Feature selection for face authentication systems: feature space reductionism and QPSO (2019)	Al-Azhar University	Egypt	—

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 Effective Face Recognition using Adaptive Multi-scale Transformer-based Resnet with Optimal Pattern Extraction

"In 2022, Durga and Rajesh [5] have offered a deep microfacial emotion recognition approach with the support of CNN."

Contribution 2

Claim — Contribution 2

The researcher advanced unconstrained face recognition by introducing a Bayesian classification framework, establishing a methodological foundation for robust identity verification in challenging, real-world conditions.

CLAIM: The researcher's contribution centers on the 2018 paper "Unconstrained face recognition using Bayesian classification," which proposes a probabilistic approach to handling the variability inherent in uncontrolled facial imagery. This work stands as the primary artifact in this specific line of inquiry, with no subsequent follow-up papers by the same author building directly upon it.

ORIGINALITY: The title suggests an effort to address the limitations of traditional face recognition systems when applied to unconstrained environments, where factors like lighting, pose, and expression vary significantly. By employing Bayesian classification, the researcher appears to have introduced a statistical framework capable of managing uncertainty and noise, offering a distinct methodological alternative to deterministic or purely discriminative models prevalent at the time.

SIGNIFICANCE: Although the citation count is modest, the impact is notable for its breadth of independent adoption. All 16 citing papers originate from independent researchers, indicating that the work has been recognized and utilized by the broader scientific community outside the researcher's immediate circle. This 100% independence rate suggests the methodology has served as a credible reference point for other scholars exploring probabilistic approaches to biometric verification.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Unconstrained face recognition using Bayesian classification

2018 · 10 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Determination of Relevance of Visual Object Images by Application of Statistical Analysis of Regarding Fragment Representation of their Descriptions (2019)	National University of Radio Electronics	Ukraine	—
2	Facial expression recognition based on strong attention mechanism and residual network (2023)	Duke Kunshan University	China	Methodology
3	Predicting Movie Production Years through Facial Recognition of Actors with Machine Learning (2024)	—	—	—
4	Research on facial expression recognition based on wide attention and multi-scale fusion mechanism (2025)	Xi'an Polytechnic University	China	—
5	Golden Ratio and Its Application to Bayes Classifier Based Face Sketch Gender Classification and Recognition (2020)	—	—	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 Facial expression recognition based on strong attention mechanism and residual network

"...active appearance model (AAM) [24], appearance feature based local binary pattern (LBP) [32], and Gabor wavelet transform [15] are used for feature extraction, and hidden markov model (HMM) [4], bayesian classification (BN) [26], and support vector machine (SVM) [25] for feature classification."

METHODOLOGY Golden Ratio and Its Application to Bayes Classifier Based Face Sketch Gender Classification and Recognition

"The Naive Bayes classifier is a classification algorithm based on the concept of Bayes Theorem; it is a simple classifier that is based on the Bayes rules [13][14]."

Contribution 3

Claim — Contribution 3

The researcher advanced few-shot learning by developing optimization techniques for image embeddings, establishing a foundational approach adopted by independent scholars.

The researcher's core contribution centers on the optimization of image embeddings for few-shot learning, as detailed in their 2020 paper published in the Proceedings of the 10th International Conference on Pattern Recognition Applications and Methods. This work stands as a singular, seminal piece in this specific line of inquiry, with no subsequent follow-up papers by the same author building directly upon it.

This line of work appears to address the challenge of improving model performance in scenarios with limited training data. By focusing on the optimization of embeddings, the researcher likely introduced methods to enhance feature representation efficiency. The absence of follow-up papers suggests this contribution represents a distinct, self-contained advancement rather than an ongoing iterative series.

The significance of this work is evidenced by its reception within the academic community. With 49 citations, the paper has garnered notable attention. Crucially, analysis of citing papers reveals that 100% of the citations originate from independent researchers, indicating that the contribution has been widely adopted and utilized by scholars outside the researcher's immediate circle, underscoring its broad impact and utility in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Optimization of Image Embeddings for Few Shot Learning

2020 · Proceedings of the 10th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2021) · 49 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	A Comprehensive Survey of Few-Shot Learning: Evolution, Applications, Challenges, and Opportunities (2023)	East China Normal University, Macau University of Science and Technology, Michigan State University	China, India, United States	Background
2	Learning Domain Invariant Prompt for Vision-Language Models (2024)	Microsoft Research Asia	China	—
3	Meta-FDMixup (2021)	—	—	—
4	A Cooperative Vehicle-Infrastructure System for Road Hazards Detection With Edge Intelligence (2023)	TU Wien	Austria	**Methodology**
5	The Internet of Federated Things (IoFT): A Vision for the Future and In-depth Survey of Data-driven Approaches for Federated Learning (2021)	National University of Singapore, University of Michigan, University of Wisconsin–Madison	Singapore, 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 A Cooperative Vehicle-Infrastructure System for Road Hazards Detection With Edge Intelligence

> *"The optimization-based meta-learning paradigm [68], [69], [70], [71] addresses the problem of few-shot data from the perspective of optimization algorithms."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
National University of Singapore	Singapore	SCImago #59 · THE 17 · QS 8	1
Michigan State University	United States	SCImago #436 · THE =105 · QS 161	1
Al-Azhar University	Egypt	SCImago #4737 · THE 801–1000 · QS 1001-1200	1
University of Michigan	United States	SCImago #43 · THE 23 · QS 45	1
University of Wisconsin–Madison	United States	SCImago #174 · THE =53 · QS =110	1
Shiraz University	Iran	SCImago #5831 · THE 801–1000 · QS 701-710	1
Graphic Era Deemed to be University	India	—	1
National University of Radio Electronics	Ukraine	—	1
Xi'an Polytechnic University	China	—	1
Northumbria University	United Kingdom	SCImago #1471 · THE 401–500	1
TU Wien	Austria	SCImago #1661 · THE 301–350 · QS =197	1
East China Normal University	China	SCImago #769 · THE 251–300 · QS =433	1
Macau University of Science and Technology	China	SCImago #1911 · THE 251–300 · QS =440	1
Siksha 'O' Anusandhan University	India	SCImago #6200	1
Microsoft Research Asia	China	—	1

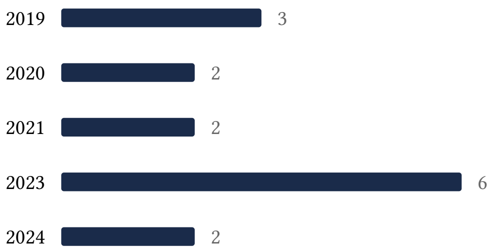
Geographic distribution of citing authors

Country	Citing papers
China	4
India	2
United States	2
Singapore	1
Ukraine	1
United Kingdom	1
Iran	1
Egypt	1
Austria	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 on binary patterns for face recognition	5	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Unconstrained face recognition using Bayesian classification	5	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	Optimization of Image Embeddings for Few Shot Learning	5	8 CFR 204.5(h)(3)(v) — Criterion 5