Scientometric Analysis of Research Trends and Emerging Frontiers in Facial Age Estimation

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ABSTRACT: Facial age estimation (FAE) has become an important part of current computer vision systems, and has applications in security, digital identity validation, healthcare, and human-computer interaction. Despite the high rate of methodological development, a holistic view of the research landscape, the patterns of collaboration, and emerging frontiers of FAE is still limited. This study presents a scientometric analysis of FAE research by using 378 publications retrieved from the Scopus database with the use of a keyword-based search strategy, by title, abstract and keywords, covering the time period 2008-2025. The dataset comprised journal articles and conference papers which were peer-reviewed. Following a structured screening process, a total of 328 documents were kept for detailed analysis using a software called VOSviewer. The publication trends, country contributions, institutional collaboration, author networks, and keyword co-occurrence and co-citation structures are analyzed in the study. The result shows that China is leading the field in terms of number of publications, with 35.3% of all publications, followed by the United States of America and India. Keyword analysis shows that deep learning, facial recognition, and feature extraction are still important themes for research and that emerging trends lean towards attention mechanisms, domain generalisation, and multimodal learning. Beyond descriptive mapping, this research offers important information about the implications of the current research trends, such as dataset bias, model generalisation issues, and deployment constraints. The results provide a systematic basis for future studies and technical design of FAE.

Keywords: Bibliometric mapping, computer vision, co-citation network, deep learning, facial age prediction, scientometric analysis.

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I. INTRODUCTION

Ageing is an irreversible process that manifests itself on the human face in terms of wrinkles, change in facial structure and textural variations. Visual characteristics of facial images such as age, gender, and facial expression have been widely used for computer vision applications (Huerta et al., 2015). Age estimation has attracted a great deal of attention in the past few years, especially in the applications of human-computer interaction, intelligent surveillance, video content analysis, soft biometric identification, and security screening (Li et al., 2016). Facial age estimation (FAE) is one of the important aspects of wellbeing in society with applications that vary from age-restricted access verification to digital identity systems. For example, it can be used to validate age for online services or purchasing age-restricted products, which is a secure and privacy-aware alternative to the conventional methods of identity verification. In addition, FAE has applications in telemedicine, in which perceived age can be used as an indicator of biological ageing and overall health status (Liu et al., 2015). Despite its wide applicability, estimating age from facial images is a very difficult problem (Zhao and Li, 2025). This challenge stems mainly from the complexity and great variability of the ageing process. As individuals age, their facial appearance gradually changes but these changes are not the same across different individuals. Although people of similar ages may have similar characteristics the process of ageing varies significantly due to biological and environmental factors.

Moreover, the development of the face differs at different stages of life. Structural changes, including bone development, are more prominent in childhood, while skin texture change and wrinkle formation are more prominent in adulthood. Consequently, a considerable gap in age results in significant differences in the appearance of the face. Overall, facial ageing can be described as a non-stationary and continual process (Drobnyh and Polovinkin, 2017). Over the years, many studies have been devoted to enhancing the quality of facial age estimation models, most of which were concentrated on model design, dataset evaluation, and performance optimisation [9],(Geng et al., 2008; Han et al., 2015; Liu et al., 2015; Bao et al., 2023; Liu et al., 2025). While these approaches have mostly increased predictability, they usually focus mainly on improving the algorithms and do not offer a wider perspective of how the research field has changed in general.

In parallel to this, scientometric analysis has become a highly effective method for the systematic study of the development of scientific disciplines. It allows for the identification of research trends, research collaboration structures and new thematic areas (Sada et al., 2025). Such methods have been extensively used in many fields such as artificial intelligence, computer vision, and biomedical research

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to trace the trajectory of scientific research and guide future directions (Yu et al., 2020; van Eck and Waltman, 2010). Within the scope of age-related research, bibliometric studies have been performed in fields of research such as age estimation in dentistry, forensic age determination and anthropological ageing studies (Ponraj et al., 2023; Boedi et al., 2023; Campanacho and Alves-Cardoso, 2023; Panci and Hackman, 2023). However, despite the emergence of a substantial number of studies in the field of facial age estimation, there is still a deficiency of scientometric studies that systematically map the intellectual structure, the collaboration networks and the emerging trends in this area. Existing works are rather concentrated on algorithmic advancements, without providing an overall view of the landscape of research. As a result, there has been little understanding about critical aspects such as the structure of the research collaboration community globally, the evolution of methodologies over time, the birth of new research frontiers, and the flow of research trends into engineering knowledge and into the real world for implementation.

This gap limits the ability of researchers and practitioners to put technological advancements into context, identify opportunities for research and design robust, scalable and deployable FAE systems. Given the rapid growth rate of deep learning-based FAE models and their adoption by more real-world applications, a systematic scientometric analysis is needed to systematically map the research development, identify collaboration patterns and knowledge gaps. A comparative summary of the existing bibliometric studies and the current work is presented in Table 1, which identifies the contribution of this work.

Table 1 Comparison of Existing Bibliometric Studies and the Present Study

Study	Focus Area	Data Source(s)	Key Methodology	Engineering Insights Provided	Limitations
Sujitha Ponraj et al. (2023)	Dental age estimation	Scopus	Bibliometric analysis (VOSviewer)	Limited	Focused on forensic/dental domain; no computer vision or deployment insights
Rudi Merdietio Boedi et al. (2023)	Dental age estimation	Scopus & Web of Science	Bibliometric mapping	None	Domain-specific; lacks AI/engineering implications
Gianluca F. Nane et al. (2017)	Researcher age prediction	Bibliometric datasets	Statistical/bibliometric analysis	None	Not related to facial age estimation or computer vision
Vítor Campanacho et al. (2023)	Anthropologica l ageing	Scopus	Bibliometric + content analysis	Limited	No focus on machine learning or facial analysis
Valentina Panci & Lucy Hackman (2023)	Forensic age estimation	Scopus	Bibliometric review	Limited	No integration with AI/computer vision systems
Ying Yu et al. (2020)	General scientometric (COVID-19)	Scopus	VOSviewer-based mapping	None	Not domain-specific to FAE
Nees Jan van Eck & Ludo Waltman (2010)	Scientometric methodology	N/A	Tool development	None	Provides tools, not domain analysis
This Study (Present Work)	Facial Age Estimation (FAE)	Scopus (2008-2025)	Scientometric analysis (VOSviewer)	YES	Addresses gap by integrating scientometric findings with engineering implications

As seen in Table 1, the extant bibliometric studies have been of domain-specific or methodological nature, while the present piece of work brings together the mapping of scientometric information with engineering-oriented knowledge, thus filling the gap between research trends and actual systems design To overcome these drawbacks, a comprehensive scientometric analysis of research in facial age estimation from the point of view of computer vision is presented in this paper. The contributions of this study include the following:

i. A structured scientometric analysis of the research on facial age estimation, giving a data-driven overview of the development of the research field.
ii. A comprehensive mapping of research trends around the world in terms of contribution of countries, institutions, and authors to reveal patterns of knowledge production as well as collaboration.
iii. Identification of new emerging research frontiers with keyword co-occurrence analysis, co-citation networks, focusing on developments in deep learning, attention models and generalisation methods.
iv. Integration of engineering-oriented insights, relating the scientometric findings to practical issues, e.g. dataset bias, model generalisation, computational limitations and real-world deployment issues.

The remainder of this paper is organized as follows: Section II presents the theoretical analysis, Section III presents the data collection and analysis methodology, Section IV presents the results and discussion, and Section V concludes the study.

II. THEORETICAL ANALYSIS

Facial age estimation (FAE) is a computer vision problem of supervised learning, in which the goal is to predict the age of an individual from a given facial image. Let $x \in \mathbb{R}^{H \times W \times C}$ be an input facial image and let y be the age label. The task is to learn a mapping function $f(x;\theta)$, parameterized by th, such that the predicted age $\hat{y} = f(x;\theta)$ approximates the true age. Depending upon the formulation FAE can be viewed as a regression problem or a classification problem. In the regression setting, model learning is usually a process of minimizing a loss function such as mean squared error, as given in Equation (1).

$$L_{\mathrm{MSE}} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (1)$$

where *N,* is the number of training samples. As is evident from Equation (1), the goal is to minimise the squared difference between the predicted age values and the true age values. Alternately, in classification-based approaches, discrete age groups are predicted by model learning and is guided by the cross-entropy loss function which is given in Equation (2):

$$L_{\mathrm{CE}} = -\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\log(\hat{y}_{i,k}) \quad (2)$$

where K represents the number of age classes. As seen in Equation (2), the model learns to maximize the probability of the correct age class. The main challenge in FAE comes from the non-linear and non-stationary nature of the ageing process that occurs through various complex variations in facial texture, shape and structural features over time (Drobnyh and Polovinkin, 2017). These variations are affected by genetic, environmental, and lifestyle factors such that there is considerable intra-class variability and inter-class similarity. Consequently, good models must be able to capture both local high-resolution features such as wrinkles and skin texture as well as global features related to facial morphology. Early theoretical theories used feature extraction performed by hand and statistical learning techniques. For example, the Ageing Pattern Subspace (AGES) model (Geng et al., 2008) modeled ageing using a temporal sequence of facial changes in the framework of a subspace. Similarly, regression-based and manifold learning methods (Han et al., 2015; Tian et al., 2021) tried to model the relationship between facial features and ages by projecting high dimensional data into low dimensional representation. While these methods yielded important theoretical and vital insights, their performance was constrained using manually engineered features.

The introduction of deep learning, and convolutional neural networks (CNNs) in general, represents a major turn in the direction of data-driven representation learning. CNN-based models can automatically learn hierarchical representations of features that would allow the extraction of low level and high-level patterns directly from facial images (Krizhevsky et al., 2012). This advancement led to a great improvement in prediction accuracy and robustness. More advanced ones, such as the divide-and-conquer strategy proposed by Zhao and Li, simulate the ageing process as a series of local stationary sub-processes, so that specialised models can learn age-specific representations better.

Even with all these improvements, deep learning models are often limited in their ability to generalise due to dataset bias and also domain variability. To solve this problem, methods such as domain-invariant learning have been proposed. For example, in a work published by Bao et al. (Bao et al., 2023), they proposed a framework which learns features which are invariant to any dataset-specific characteristics, hence increasing the performance within a cross-domain scenario. This underlines the need to create models that are not only accurate but also robust to different distributions of data. Recent improvements to this include attention mechanisms and transformer-based architectures to further the improvement of the features. Global and Local Aware (GLA-Age) model (Liu et al., 2025) for example uses spatial attention to attend to the regions of the age-relevant parts of facial images and capture the long-range dependencies in the images. This is part of a more general trend towards more context aware models that can incorporate both local and global information.

Beyond the development of algorithms, the origin of FAE research needs to be viewed from a higher-level analytic perspective. Scientometric analysis is such a framework that provides the quantitative analysis of the patterns in scientific publications, citation networks, and keyword relationships (Ponraj et al., 2023; Yu et al., 2020). Let $D = \{d_1, d_2, \ldots, d_n\}$ be a set of publications and $K = \{k_1, k_2, \ldots, k_m\}$ be a set of keywords. Keyword co-occurrence associations may be modeled as a network.

$$G = (K, E) \quad (3)$$

where E is the edges equals to frequency of co-occurrence between keywords.

As it is seen in Equation (3), this network structure helps in detecting dominant themes and relationships in the research field. Similarly, co-citation analysis models the intellectual structure of the domain in terms of how often pairs of references are cited together, to get a sense of the foundational studies and changing research directions. Overall, the theoretical basis of the present work combines both the algorithmic development of facial age estimation models, and the scientific method required for their scientometric analysis. This dual perspective adds a rigorous basis for the methodology, and an in-depth interpretation of the results presented in this study.

III. MATERIALS AND METHODS

This study uses the scientometric approach to examine research trends in facial age estimation (FAE) in the field of computer vision. Publications over a seventeen-year period (2008-2025) were retrieved from the database, Scopus, and analysed using VOSviewer. The analysis was conducted based on multiple dimensions such as contribution by countries, journals, institutions, and authors, keyword co-occurrence and co-citation networks. The overall workflow, depicted in Figure 1, was undertaken in a series of stages. Initially, relevant literature was identified using database selection and keyword-based searching and the resulting records were screened to exclude unrelated records. The refined dataset was then applied for scientometric analysis. This analysis involved co-authorship, institutional collaboration, keyword mapping, and co-citation analysis which led to interpretation of results.

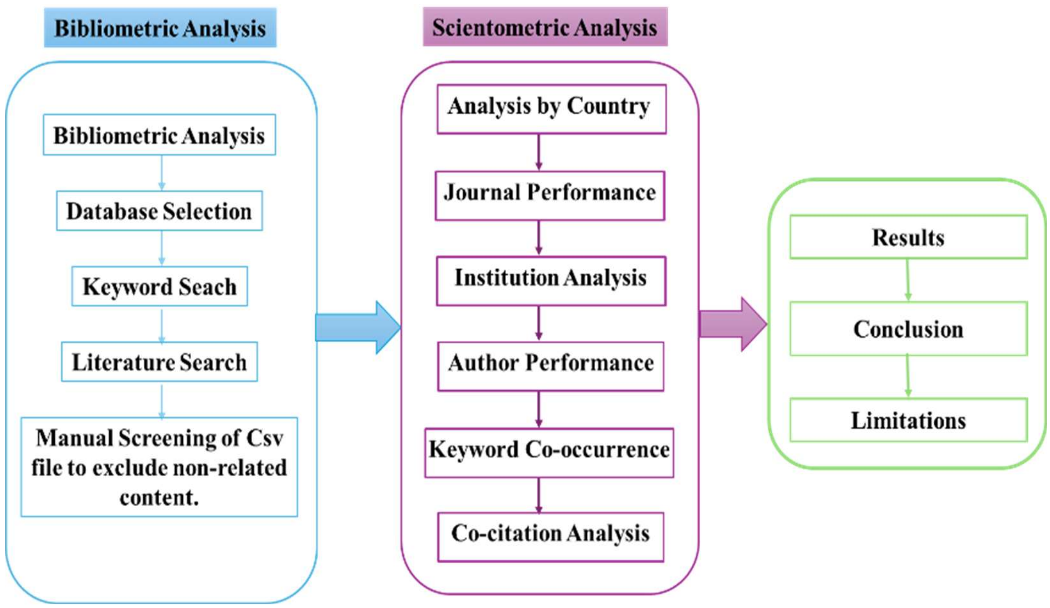

Figure 1 Overview of the research methodology

A. Sector Data Collection and Search Strategy

The database chosen as the first source of literature is the SCOPUS database because of its large coverage of computer vision and image processing research when compared to other databases such as the Web of Science, Google Scholar and PubMed (Mongeon and Paul-Hus, 2016). As an all-round citation indexing platform, SCOPUS enables efficient retrieval and analysis of scholarly publications, not only journal articles and conference proceedings, and to ensure sufficient coverage of relevant studies, a keyword search strategy was adopted for the search. Publications were included if the defined search terms were included in the Title, Abstract or Keywords field. search query is as shown below.
(“Facial Age Estimation*” OR “Face Age Estimation*” AND (“Prediction*”))

The wildcard operator () was used to catch variation of keywords and hence make retrieval completeness better. The search was set up using the TITLE-ABS-KEY option in the journal database known as Scopus. The search period was from 2008-2025 and data extraction was performed on 22 March 2025. all retrieved records contained complete bibliographic information and in-text citations. It should be noted that the search query was intentionally restricted to maintain a focused scope on facial age estimation; therefore, related studies using broader or alternative terminologies may not have been captured which represents a limitation of this study.

B. Data Screening and Cleaning

Following data retrieval, a structured screening process was applied to refine the data set. Only peer-reviewed journal articles and conference papers published between 2008 and 2025 and in English were considered if they had facial age estimation related keywords in the title, abstract or keywords. Data cleaning was carried out through Microsoft Excel 2023 wherein duplicate data, irrelevant studies and non-scholarly publications such as editorial, notes, or short communications without any empirical contribution were excluded. Following the application of these criteria 328 documents were retained from the initial set of 378 records for further analysis.

C. Scientometric Analysis

The cleaned dataset was imported in VOSviewer to further undertake network-based scientometric analysis. As described in (van Eck and Waltman, 2010), bibliometric techniques are a quantitative way of examining the structure and development of the domains in scientific research. In this study, VOSviewer was set as shown in Table 2 to create several types of networks such as co-authorship, keyword co-occurrence, citation and co-citation networks. Careful attention was placed on the selection of threshold in order to balance clarity and analytical relevance (Yu et al., 2020). The co-authorship analysis examined the patterns of collaboration between authors, institutions, and countries. Authors were included if at least two publications were published by the author. 22 authors met this, of the 286 authors. Similarly, organizations were to have a minimum of two publications, resulting in 51 organizations out of 575. For countries, a five publications threshold was imposed, in which case 22 countries met this condition out of 53.

The co-occurrence analysis was conducted on keywords, both author-provided keywords and indexed keywords. A minimum occurrence threshold of five was applied resulting in 146 keywords of 2043 keywords were retained. This approach guaranteed that only the often occurring and thematically important keywords were taken into consideration. The Analysis of Citation has been carried out for the journals and sources, a minimum threshold of 20 citations. A total of 75 sources satisfied this criterion of 328: the most influential publication venues. The co-citation analysis was used to investigate relationships between cited references using a threshold of five co-citations. This led to 115 references being chosen from a total of 8730, which can give insight into the basic literature of the field.

Table 2 VOSviewer Settings

Type of analysis	Unit of analysis	Threshold	Threshold m	Total number retrieved
Co-Authorship	Authors	Min of 2 docs by an author	22	328
	Organization	Min of 2 docs by an organization	51	575
	Countries	Min of 5 docs by a country	22	53
Co-occurrence	All Keywords	Min of 5 keywords per doc	146	2043
Citation	Sources/Journals	Min num of citations 20	75	328
Co-citation	Cited References	Min num of 5 cited references	115	8730

These threshold settings were useful in trying to focus the analysis on patterns that were meaningful to the analysis and also helped to minimize the impact of sparse or weakly connected data.

D. Reproducibility Framework

To improve transparency and reproducibility, all steps of the methodology were clearly described, such as the choice of the database, keyword search strategy, screening procedures, and analytical tools. The use of services such as SCOPUS and the use of clearly defined search queries and filtering criteria enable the retrieval process of the datasets to be replicated. In addition, the combination of Microsoft Excel for data cleaning and VOSviewer for network analysis guarantees a structured and repeatable process, which is in line with established scientometric practices (Yu et al., 2020; van Eck and Waltman, 2010).

IV. RESULTS, DISCUSSION AND ENGINEERING IMPLICATIONS

This section provides the scientometric result of the research work on facial age estimation (FAE) and gives a critical interpretation of the patterns observed. Beyond descriptive analysis, the findings also are further interpreted to emphasize its implications for system design and deployment as well as future research directions.

A. Country-Level Research Performance

The analysis as described in Figure 2 shows China, the United States and India as the major contributors in FAE research with China publishing the highest number of articles. The present large node size associated with China from Figure 3, suggests both a high publication output and a strong bibliographic influence. Citation bursts observed across several countries also reflect the dynamic and rapidly evolving nature of the research landscape. China has the advantage of significant government investment in AI-based systems, especially in surveillance and public safety, access to large-scale data sets and partnerships between academia and industry (Gao et al. 2025). The United States maintains their leadership because of their robust research funding and open innovation ecosystem and the contributions of major technology firms (Task Force, 2023).

The reason India is growing is because of its various population, the growing ecosystem of AI and the national initiative of its AI (Government of India, 2018). The concentration of the amount of research output in a few countries implies that FAE datasets and models often get developed in a region-specific context. The United States is the leader through robust research funding, open innovation ecosystem and contributions from major technology firms (Task Force, 2023). The reason India is growing is because of its various population, the growing ecosystem of AI and national initiative of its AI (Government of India, 2018). The concentration of the amount of research output in a few countries implies that FAE datasets and models often get developed in a region-specific context. This has direct implications for dataset bias and fairness as models trained on datasets concentrated in geographical locations may not generalise well across different populations. For these reasons, the future design of such systems will need to prioritize the global representativeness of datasets and cross-domain validation approaches.

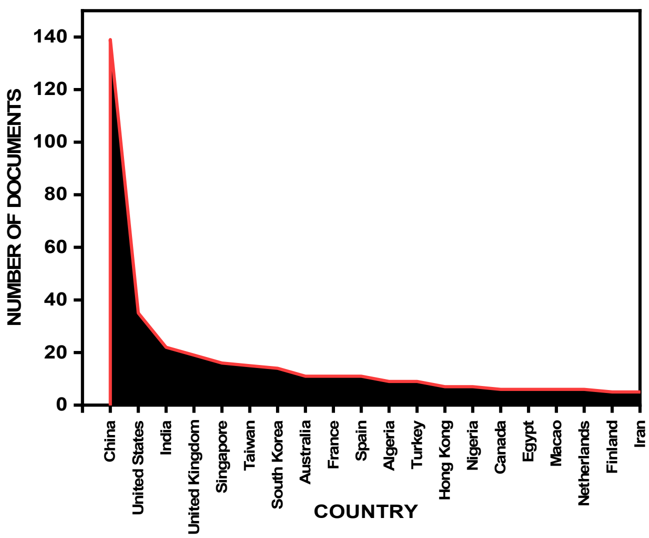

Figure 2 Number of documents produced by the top 20 countries

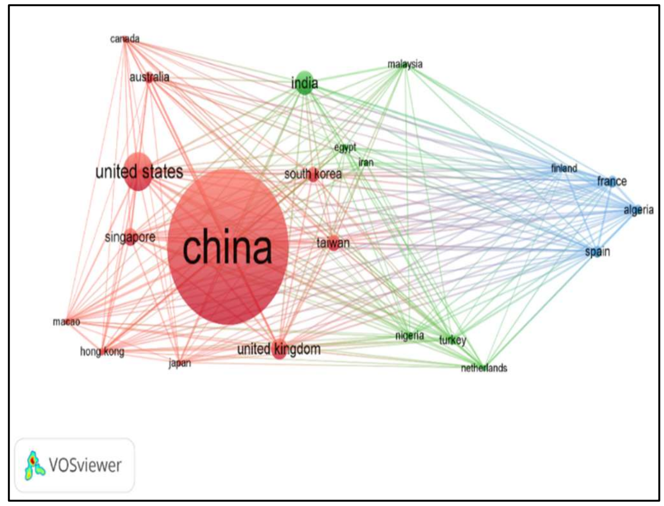

Figure 3 Performance of Countries

B. Source (Journal and Conference) Analysis

Several high-impact journals have been identified as journals that routinely publish FAE studies. This is acquired by looking at the journals that have the most publications and their percentages. With 134 articles published, Lecture Notes in Computer Science is the leading source with 27.61% and followed by Proceedings - International Conference on pattern recognition and International Conference on Acoustics, Speech, and Signal Processing which account for 5.97% and 5.22%, respectively. The table also suggests that there is variation in the research environment for FAE. Journals cover a wide range of topics from multimedia and machine learning to acoustic, voice processing and signal processing research

Table 3 Number of relevant articles and percentage of total publication per source

Sources (Journals and Conferences)	Relevant articles	Total articles (%)
Lecture Notes in Computer Science	37	27.61
Proceedings - International Conference on Pattern Recognition	8	5.97
IEEE International Conference on Acoustics, Speech and Signal Processing	7	5.22
IEEE Access	7	5.22
IEEE Transactions on Pattern Analysis and Machine Intelligence	7	5.22
IEEE Transactions on Image Processing	6	4.48
Multimedia Tools and Applications	6	4.48
Proceedings - International Conference on Image Processing, ICIP	6	4.48
Communications in Computer and Information Science	5	3.73
IEEE Transactions on Information Forensics and Security	5	3.73
Neurocomputing	5	3.73
IEEE International Conference on Multimedia and Expo	5	3.73
IEEE Computer Society Conference on Computer Vision and Pattern Recognition	5	3.73
International Journal of Advanced Computer Science and Applications	4	2.99
Pattern Recognition	4	2.99
Proceedings of SPIE - The International Society for Optical Engineering	4	2.99
Proceedings of the International Joint Conference on Neural Networks	4	2.99

IEEE Transactions on Multimedia	3	2.24
IEEE Transactions on Neural Networks and Learning Systems	3	2.24
Mathematical Problems in Engineering	3	2.24

The results show that the top source is Lecture Notes in Computer Science followed by major conferences and journals of the Institute of Electrical and Electronic Engineers (IEEE) as can be seen from Table 3. The variety of publication avenues reflects the interdisciplinary background of FAE research in the domains of computer vision, multimedia and signal processing. The control of conference proceedings reflects the speed of development of FAE methods, especially in the field of deep learning. While this boosts innovation, it can also result in a low level of standardization and reproducibility. For the sake of engineering practice, this is important for benchmark standardization and consistent evaluation frameworks to support reliable system deployment.

C. *Institutional Research Performance*

The top ten universities contributing majorly to the field of FAE research are included in Table 4 along with details on their global impact and research output. With 292 citations, the Department of Automation at Tsinghua University in Beijing is the most prolific university with the number of documents produced. The Total Link Strength column shows the networks of institutional collaboration. With a link strength of 17, the University of the Basque Country Upv/Ehu in San Sebastian, Spain has the greatest connection signifying a broad spectrum of international and inter-institution research partnership. Despite having less than 100 citations each, Iker Basque from the Basque Foundation for Science in Bilbao, Spain and Laboratory of Lesia from the University of Biskra in Biskra, Algeria both have strong collaboration (16 and 15, respectively). This points to key institutions driving breakthroughs in FAE for the basis of strategic cooperation and knowledge sharing. Future research collaborations will be much better informed by the knowledge of these leading universities.

Table 4 Performance Analysis of Research Institutions

Organization	**Documents**	**Citations**	**Total link strength**
Tsinghua University, Department of Automation, Beijing, China	4	292	0
Chinese Academy of Sciences, Institute of Automation, China	2	147	0
Nanjing University, China	2	132	2
Southeast University, Nanjing, China	2	132	2
School of Computer Science and Engineering, Southeast University, Nanjing, 211189, China	4	130	2
University of The Basque Country, Spain	6	93	17
Iker Basque, Basque Foundation for Science, Bilbao, Spain	5	84	16
Zhejiang University College, Hangzhou, China	2	84	1
National Chung Hsing University, Taiwan	3	55	4
Laboratory Of Lesia, University of Biskra, Biskra, Algeria	4	54	15
School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing, China	2	50	2
Dpdce, University Iuav, Santa Croce 1957, Venice, 30135, Italy	2	46	2
Herta Security, Pau Claris 165 4-B, Barcelona, 08037, Spain	2	46	2
Institute of Deep Learning, Baidu Research, Beijing, China	2	45	3
National Engineering Laboratory for Deep Learning Technology and Application, Beijing, China	2	45	3
Department of Computer Science, Tokyo Institute of Technology, Japan	3	39	3
Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, China	3	39	3
Laboratory of Li3c, University of Biskra, Biskra, Algeria	2	39	7
National Taiwan University of Science and Technology, Taipei, Taiwan	2	36	0
Iemn Doae Umr Cnrs 8520 Laboratory, Polytechnic University of Hauts-De-France, France	2	14	2

Strong institutional collaboration networks are indicative of knowledge sharing and co-development of methodologies but the clustering of leading institutions in particular areas can limit the diversity of datasets and approaches This in turn has implications for the robustness and inclusiveness of models and appears to call for wider international collaboration in system development.

D. *Author Performance and Collaboration Networks*

The top authors in this field of research show strong collaborative tendencies. Network analysis shows that authors from different regions tend to co-author and thus promote cross-institutional and interdisciplinary research. This cooperation is indicated by high citation numbers and total link strength. The most prolific authors contributing to the FAE research are highlighted in Figure 4. In addition, Table 5 shows authors with at least 150 citations that influence the age estimation research landscape.

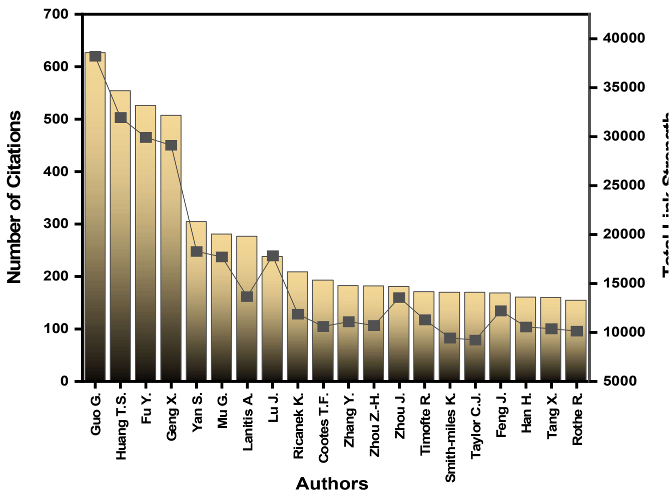

Figure 4 Performance of Authors

Guo G, of West Virginia University, is the highest cited researcher in this field and in this time frame with a total of 627 citations followed by the late Huang T.S of the University of Illinois and Fu Y, of University College London, with 554 and 526 citations respectively. The Table also shows the prevalence of Chinese writers (as shown by common Chinese names such as Zhang, Zhou and Geng), which is a signpost of China's key position and substantial investment in computer vision and pattern recognition, especially in age estimation based on facial photos. Identifying prolific authors provides useful information for developing future research collaborations, identifying authoritative competence, and recognizing prominent academic contributions that determine emergent research paths.

Table 5 Author performance showing total link strength and number of citations

Authors	Number of Citations	Total Link Strength
Guo G.	627	38209
Huang T.S.	554	31953
Fu Y.	526	29922
Geng X.	507	29115
Yan S.	304	18283
Mu G.	280	17717
Lanitis A.	276	13665
Lu J.	237	17834
Ricanek K.	208	11876
Cootes T.F.	192	10605
Zhang Y.	182	11102
Zhou Z.-H.	181	10716
Zhou J.	180	13573
Timofte R.	170	11300
Smith-miles K.	169	9440
Taylor C.J.	169	9234
Feng J.	168	12218
Han H.	160	10566
Tang X.	159	10381
Rothe R.	154	10138

The analysis shows that Guo G., Huang T.S. and Fu Y. are some of the most influential authors. For example, high values of total link strength represent high levels of collaboration among authors and institutions. The existence of author networks with a large number of interconnected nodes represents a high level of collaboration amongst leading researchers which facilitates the exchange of ideas, data sets and modelling approaches. As a result, some approaches, especially those that use deep learning models, become popular and progressively improved, which results in the consolidation of dominant methodologies within the field. Over time, this results in the consolidation of the practices of methodology, in which a small set of techniques are the basis of further research.

E. *Keyword Co-occurrence and Research Trends*

Keyword analysis suggests that "age estimation," "face recognition," "deep learning," "facial age estimation," "computer vision" and "feature extraction" are just a few of the most common terms used simultaneously. The co-occurrence network map in Figure 5 shows clusters which reflect emerging trends such as a shift to deep learning architectures and better feature extraction methods and gives an overview of the state of facial age estimation research. The interrelated clusters covering such keywords as algorithm development, human-centered applications, dataset difficulties and cutting-edge learning techniques, illustrate the multi-faced nature of the structure of the field. In addition to being an illuminating demonstration of the principal themes, this analysis suggests potentially fruitful directions for further study, in particular in the areas of advanced representation learning and multidisciplinary applications.

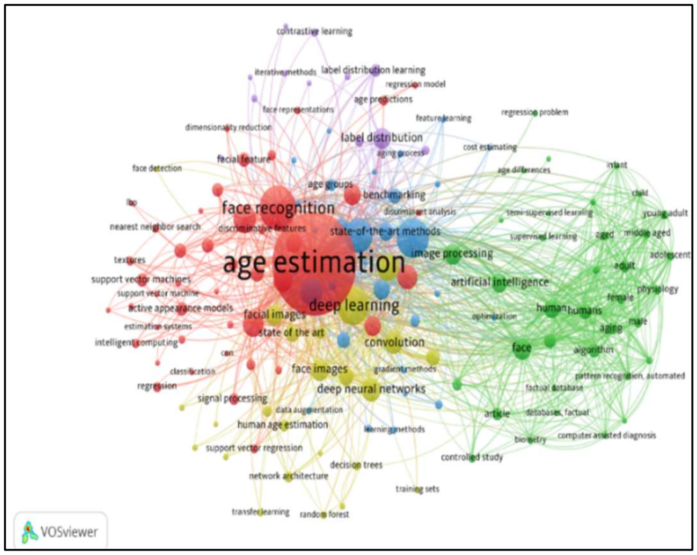

Figure 5 Network of keyword co-occurrence

The red cluster is focused on age estimation and facial image recognition, whereas the blue cluster focuses on the machine learning models used in age estimation such as deep learning and convolutional neural networks. The green cluster is related to extraction methods and algorithms. The central cluster with keywords like age estimation, face recognition, facial images, deep learning, and support vector machines are the basic subject of study that uses machine learning models and computer vision approaches to identify age using facial features. Its high degree of interconnectedness indicates the importance and centrality of the main area of research in age estimation using face analysis.

The green cluster is concerned with the biological and demographic aspects of age estimation and keywords such as human, adult, adolescent, child, infant, age differences and physiology are associated with the cluster. This shows a high interest in the problem of age estimation in real applications in human life, e.g., in development or health applications. The use of terminologies like diagnosis and pattern recognition means transdisciplinary applications related to healthcare, psychology & biometric systems. The blue cluster includes phrases such as label distribution, regression model, benchmarking and age prediction, showing an emphasis on the methodologies of modelling and evaluation of the dataset. It highlights the need to solve the issue of label imbalance, devise good paradigms for learning, and establish common criteria for comparing performance, as a contribution to the methodological strength in constructing robust age estimation systems.

The yellow cluster belongs to deep learning techniques and model optimization, which include convolution, deep neural networks, data augmentation, transfer learning, random forest, decision trees. These approaches focus on enhancing the accuracy and generalisability of the models by advanced architecture, preprocessing techniques and optimisation strategies. Even though it is smaller, the purple cluster makes it possible to underline emerging and advanced techniques such as face representations, dimensionality reduction, and contrastive learning. These techniques represent ongoing attempts to improve the accuracy and discriminative strength of the facial features that are used in age estimation, as well as pushing the limits of current performance levels.

Table 6 presents the top 20 most occurring keywords with age estimation with a total link strength of 1,571 and average publication year of 2018 and face recognition shown as the second highest with a link strength of 475. Figure 6 illustrates the relationships between these keywords based on their total link strengths

Table 6 Keyword co-occurrence

Keywords	Links	Total link Strength	Occurrences	% of occurrence	Average Publication/year
Age estimation	145	1571	251	25.9	2018
Face recognition	121	475	77	7.9	2017
Deep learning	120	448	64	6.6	2020
Facial age estimation	111	411	64	6.6	2018
Computer vision	120	399	54	5.6	2018

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Feature extraction	110	297	39	4.0	2018
Convolutional neural netw	99	339	38	3.9	2020
Learning systems	100	276	37	3.8	2019
Classification	105	284	35	3.6	2019
Neural networks	96	286	33	3.4	2018
Deep neural networks	95	277	32	3.3	2019
Regression analysis	89	225	32	3.3	2017
Convolution	89	259	29	3.0	2019
Face	99	405	28	2.9	2018
Face images	84	222	28	2.9	2016
Biometrics	75	174	26	2.7	2015
Facial images	76	177	26	2.7	2018
Label distribution	83	188	26	2.7	2018
Estimation	87	201	25	2.6	2013
Image processing	101	272	25	2.6	2017

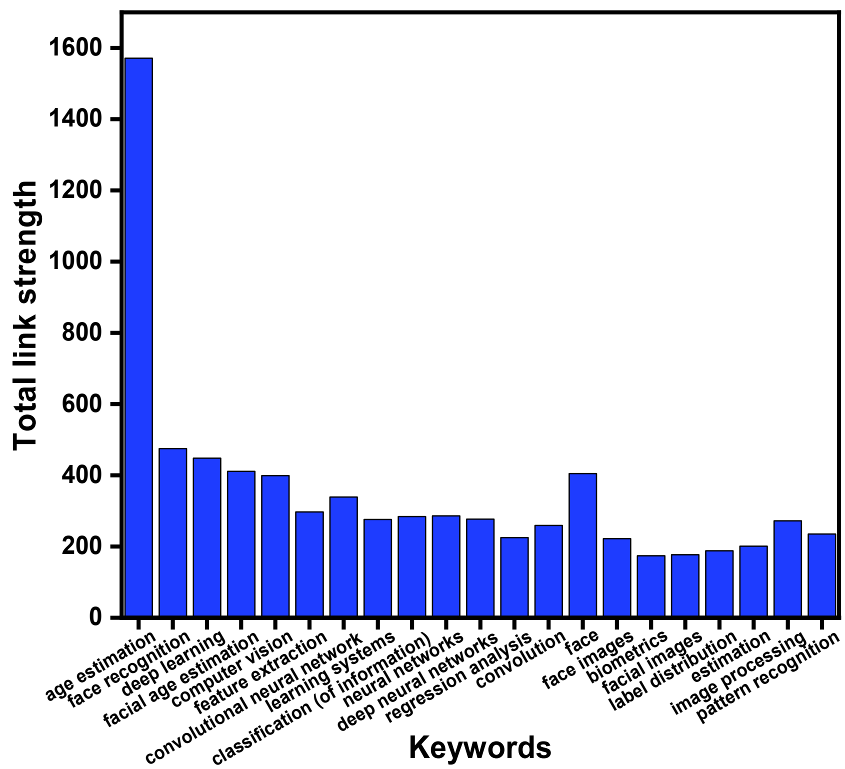

Figure 6 Twenty most re-occurring keywords

F. Cited references and Co-citation Analysis

Figure 7 shows the co-citation network that demonstrates the intellectual organization of the research on facial age estimation (FAE) by clusters of commonly co-cited references. The size of nodes and the density of links are used to show the impact of influential works and the strength of their connection in literature. As indicated in Table 6, Geng et al. (2007) and Lanitis et al. (2002) are the most co-cited (19 citations each) as they provide a pioneer contribution to the modelling of the facial ageing patterns based on statistical methods. On the same note, Fu et al. (2010) and Geng et al. (2013) with 18 citations each represent the shift to more sophisticated learning models, such as survey-based insights and label distribution learning. A definite evolution of methodological approach is depicted by the network structure. Earlier research works are placed in the middle, which means that they impacted future research, whereas more recent ones, like Dong et al. (2016) and Zhang et al. (2016) are related to deep learning-based methods. The use of deep convolutional neural networks to extract features and learn the representations can be further evidenced using 17 citations in Simonyan and Zisserman (2014).

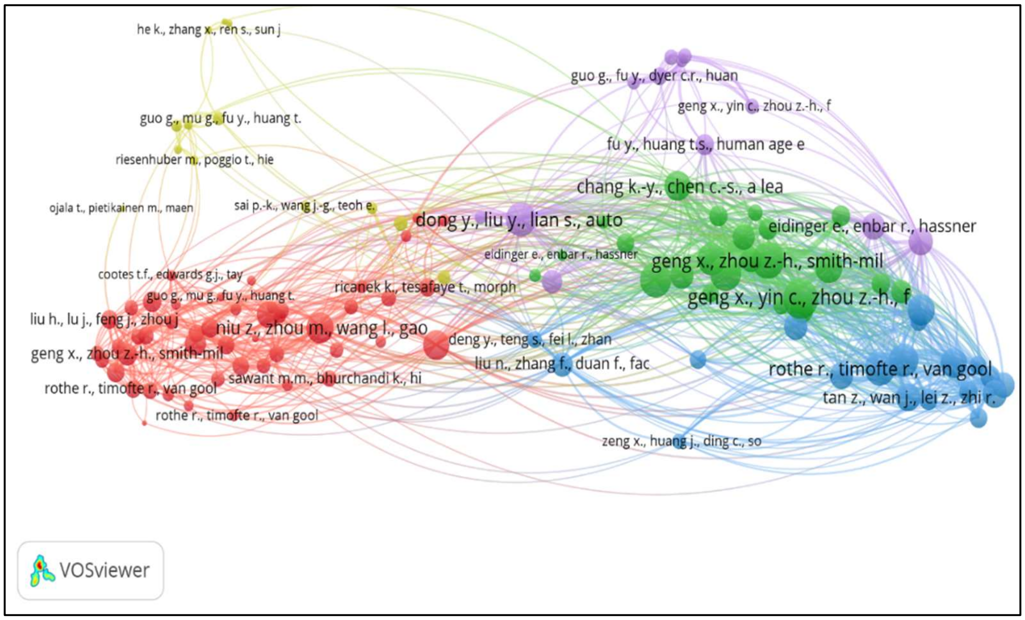

Figure 7 Co-citation network analysis by cited references

Table 7 Co-citation network by cited references

S/N	Cited References	No. of Citations
1	Geng X., Zhou Z.-H., Smith-Miles K., Automatic Age Estimation Based on Facial Aging Pattern Transactions on Pattern Analysis and Machine Intelligence, 29, 12, pp. 2234-2240, (2007)	19
2	Lanitis A., Taylor C.J., Cootes T.F., Toward Automatic Simulation of Aging Effects on Face Ir IEEE Transactions on Pattern Analysis and Machine Intelligence, 24, 4, pp. 442-455, (2002)	19
3	Dong Y., Liu y., Lian S., Automatic Age Estimation Based on Deep Learning Algc Neurocomputing, 187, pp. 4-10, (2016)	18
4	Fu Y., Guo G., Huang T.S., Age Synthesis and Estimation Via Faces: A Survey, IEEE Trans. I Anal. Mach. Intell., 32, 11, pp. 1955-1976, (2010)	18
5	Geng X., Yin C., Zhou Z.-H., Facial Age Estimation by Learning from Label Distributions, IEEE Pattern Anal. Mach. intel., 35, 10, pp. 2401-2412, (2013)	18
6	Simonyan K., Zisserman A., Very Deep Convolutional Networks for Large-Scale Image Recog (2014)	17
7	Geng X., Zhou Z.-H., Smith-Miles k., Automatic Age Estimation Based on Facial Patterns, IEEE Pattern Anal. Mach. Intell., 29, 12, pp. 2234-2240, (2007)	16
8	Zhang K., Zhang Z., Li Z., Qiao Y., Joint Face Detection and Alignment Using Multitask Cas Convolutional Networks, IEEE signal process. Lett., 23, 10, pp. 1499-1503, (2016)	16
9	Fu Y., Huang T.S., Human Age Estimation with Regression on Discriminative Aging Manifold, Transactions on Multimedia, 10, 4, pp. 578-584, (2008)	15
10	Guo G., Fu Y., Dyer C.R., Huang T.S., Image-based Human Age Estimation by Manifold Learnii Locally Adjusted Robust Regression, IEEE Trans. Image Process., 17, 7, pp. 1178-1188, (2008)	15

G. *Synthesis of Findings and Practical Implications*

The results, combined, show that the field of research in facial age estimation (FAE) is developing quickly, where a few countries, institutions, and authors are producing the bulk of results. The use of deep learning techniques and the use of benchmark datasets have been widely adopted, which has led to significant improvements in predictive performance. However, these advancements have also come with some important challenges, specifically regarding dataset bias, model generalisations, and also the limitations of deploying these models in real-world scenarios.

From an engineering point of view, the direct inferences of these implications can be readily inferred from the patterns in scientometry that may be observed in this study. The polarization of research output among a relatively small number of countries and institutions, evident in the country- and institutional performances revealed in the above analyses, implies that a large number of frequently used data sets and models are produced in region-specific contexts. This raises concerns about the bias in datasets and the need for more diverse and representative datasets that capture variations across populations and environments. Furthermore, the keyword co-occurrence analysis shows that deep learning, face recognition, and feature extraction techniques are strongly dominated. While these approaches have made important improvements in predictive accuracy, their use of benchmark datasets plays a part in challenges of cross-domain generalisations. This is further supported by the co-citation analysis which shows a clear trend towards high-capacity deep learning models. Although such models are effective, they suffer from growing complexity, which poses constraint issues regarding computational efficiency, scalability, and time-stamped deployment.

In addition, the strong collaboration patterns found among leading authors and institutions in the institutional and author collaboration analyses indicate the ubiquity and reinforcement of similar methodologies. While this promotes rapid advancements, it can narrow down possible methodologies and prevent trying alternative approaches. There is a need to pay attention to the development of more generalisable models, efficient architectures, which are suitable to be deployed in resource constrained environments, and evaluation strategies which go beyond controlled datasets. Overall, these insights provide an evidence-based basis to inform future research and engineering decisions on the design, evaluation and deployment of facial age estimation systems.

V. CONCLUSION

Facial age estimation has been a hot topic in the field of computer vision with applications in human-computer interaction, security and surveillance. This study aimed to present an overview of the scientific approach for facial age estimation, from 2008 to 2025, and to conduct a scientometric analysis of publications on the subject, retrieved from the Scopus database and 378 publications that were stored after the selection was chosen. The research trends, collaboration patterns, and the development of the major research themes were analyzed with VOSviewer.

The results show a high number of countries, institutions and authors with a high concentration of research output, as well as a dominant focus on deep learning approaches and benchmark datasets. While these developments have made a significant impact on improving predictive performance, they also point to some important challenges associated with the bias in the datasets, model generalisation, and deployment constraints. Beyond the significance of charting the research landscape, there are insights from engineering that are applicable to the design, evaluation and introduction of practical facial age estimation systems.

Based on these findings, it is natural for several important directions of future research to emerge. Reliance on centralised datasets raises data privacy and access-related issues, which hints at the potential for federated learning approaches to train models in a distributed fashion. Furthermore, the preponderance of facial image-based methods speaks to the need for multi-modal systems that combine other data sources in order to improve robustness and accuracy. The concentration of research in certain datasets and areas that were observed, also grasps the need for developing more inclusive datasets and bias mitigation strategies. Finally, with more and more complex models, there is a need to optimise them for real-time deployment, especially in resource-constrained environments.

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AUTHORS' CONTRIBUTIONS

F.A Ilyasu: Conceptualization, data collection, analysis, methodology, and writing- Original draft.
S.A. Adeshina: Supervision, conceptualization, review, and editing. All authors read and approved of the final manuscript.

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