# Navigating the New Normal: A Bibliometric Analysis of Masked Face Recognition Research Using VOSviewer and Biblioshiny

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*Face recognition is a technique that has dominated in several fields such as security, surveillance, and biometric identity. However, the recent global health crisis, particularly the COVID-19 pandemic, has led to a growing need for face recognition systems that can accurately identify people even when they are wearing masks. This bibliometric study utilizes VOSviewer and Biblioshiny to conduct a comprehensive analysis of masked face recognition research trends from 2018 to 2024. The study focused on understanding the recent developments in masked face recognition research. By searching Scopus database, we found a significant increase in research activity on this topic starting around 2019. This increase is likely due to the COVID-19 pandemic, which made it more important to develop technology that can identify people even when they are wearing masks. We identified the top institutions, authors, and countries contributing to this research and the dominant themes and collaborations. Our findings demonstrate a 250% increase in publications from 2019 to 2024, focusing on deep learning techniques and pandemic-specific applications. Network analysis identified the Fraunhofer Institute and Chinese universities as key players in the field. These results provide clear view into the global distribution of research efforts, the evolution of masked face recognition technology, and its societal impacts, offering a foundation for future innovation and policy development.*

*Povzetek: Opisana je bibliometrična analiza raziskav o prepoznavanju obraza z masko z uporabo VOSviewer in Biblioshiny. Identificirane so bile ključne raziskovalne institucije in 250-odstotni porast objav v obdobju (2019–2024).*

## 1 Introduction

Facial recognition systems [1] record, analyze, and compare patterns of an individual's face, making identification and authentication of persons from their faces at hand. As one of the most secure methods for verifying identity, facial recognition technology, alongside other biometric technologies, offers significant potential. It is less susceptible to theft and provides greater security compared to traditional passwords generated by users.

Face recognition is the ability of a program to identify a person from a given image or video feed containing an individual's face. During the last few years, face recognition has seen colossal advances pushing progressive performance close to humans, typically surpassing human capabilities [2] [3]. The advancement in Face recognition has been directed by profound deep learning architectures somewhat recently. This exploration article outlines advancements in profound neural networks and examines cutting-edge CNN-based face recognition frameworks. The face offers a wealth of distinctive features that can reveal a person's identity, which can be extracted in various unobtrusive and unrestricted settings [4] . Automated face recognition has vast practical applications, harnessing these features for various purposes.

However, due to the diversity of facial features, mapping faces becomes complex and challenging. Deep Learning, a subset of Machine Learning, revolves around using artificial neural networks with multiple layers to extract more complex features from data progressively. DL employs multiple processing layers to learn data representation, each level extracting increasingly sophisticated features. Since 2014, face recognition has undergone a paradigm shift due to this transformative technology. Human face recognition has become one of the most active research domains. Masked face recognition is an interdisciplinary research topic spanning diverse fields such as computer science, machine learning, biometrics, ethics, and public health [5]. It is important to note that the selected databases for bibliometric analysis may not fully encompass the interdisciplinary scope of this emerging field. This area of focuses on the ability to recognize and identify people even when they are wearing facial masks. For many reasons this approach has gained a significant influence in including public health initiatives such as mask requirements, safety considerations etc.

Within the fields of biometrics and computer vision, extensive research has been conducted on facial recognition. The primary goal of facial recognition is to uniquely identify and verify individuals based on their facial features. Traditional facial recognition systems were originally designed to identify people without any obstructions. The COVID-19 epidemic emphasized the urgent need for facial recognition systems to adapt the need for masked face recognition.

Masked face detection can be employed in law enforcement and surveillance to identify individuals wearing masks, potentially assisting in criminal investigations. The widespread adoption of face detection systems by companies like Google has raised ethical concerns regarding identity, consent, and surveillance. Recent advancements in computer technology like deep learning have significantly improved the ability of machines to understand and interpret visual information. This has led to significant improvements in facial recognition systems, especially for masked face recognition. [6].

Masked face recognition has become a prominent area of interest and research during the COVID-19 pandemic, presenting unique challenges in computer vision and biometrics [6] [7]. The main challenge is to develop precise and robust methods for recognizing and localizing masked faces in images or video streams.

Face recognition systems which were introduced way before the advent of face masks will face a considerable decline in the performance after the introduction of face masks. The speed and accuracy of the existing face recognition algorithms might be affected negatively due to this. There is a challenge in creating complex and large datasets comprising of unmasked and masked faces. For the development and testing of face recognition algorithms, these diverse and large datasets are required. For creating robust models, we require superior categorized data which includes lighting conditions, different type of masks and various backgrounds. Then there is the question of using of devices for masked face detection which generates moral and privacy demands, predominantly in public or private realms. We face a laborious challenge in making an equilibrium between privacy and safety, all the while maintaining and guaranteeing rights of the individual.

Recent studies have developed computer programs that can identify people even when they are wearing masks. To direct future research, it is essential to understand the most recent advancements in this field. Examining the previous studies on masked face recognition can provide important information about a real-world problem and highlight advances in technology. This research reveals the importance of working with experts from different domains and considering ethical issues when developing and using masked face recognition technology.

Overall, there is a question of morality and law when it comes to facial recognition even with masks. Bibliometric analysis can provide insights into on how researchers address ethical concerns related to facial recognition, which can help shape the creation of ethical standards and laws. This bibliometric analysis would provide insight into masked face recognition research and development, focus on influential authors and fields for further investigation. Clearly, researchers carrying out such an analysis need to be informed regarding the constraints and limitations in order for them to draw proper conclusions from the results. Masked face recognition articles and papers are gathered together. Metrics such as number of publications, citations and pattern variables for the authors, words or keywords thus used and collaborative matrix are studied.

Bibliometrics is essential for researchers to find patterns and effects in the literature of academia [8] [9] [10]. In many cases the field is often used while doing research on metadata, such as patterns of authorship and citation [11] [12] [13]. Two of the simplifying processes are VOSviewer and biblioshiny. The VOSviewer application is centered on the development of user-friendly visualizations of bibliometric networks, providing metadata information about co-authorships, citations and map domains [14] [15] [16]. Indeed, biblioshiny – an easy-to-use user interface for the R package of Bibliometrics - provides a complete system that enables researchers to conduct science map analysis. Both tools perform data analysis and provide visualization of scholarly information; however, their implementation often depends on the user's knowledge about R as well as individual research needs [17] [18] [19].

## 2 Review of literature

Facial recognition, a branch of computer vision and biometrics [20], utilizes facial features for individual identification. It involves analyzing images or videos to identify individuals [21]. While more difficult to gather, faces represent identity better than iris scans [22]. The study of masked faces is a multidisciplinary field involving computer science, machine learning, biometrics, ethics, and public health [5]. Accurate and reliable facial recognition technologies are essential for identifying individuals wearing masks.

The widespread use of face masks during the pandemic has presented a significant challenge for facial recognition systems. Masked face recognition has emerged as a critical research area due to its potential applications in healthcare, security, and public health. So, researchers are working hard on figuring out how to make computers recognize faces even when the mask covers part of the faces.

The recent significant progress in face recognition algorithms can be attributed to the remarkable advancements in deep learning. The performance of facial recognition systems can degrade significantly in uncontrolled environments due to factors such as facial expressions, pose variations, occlusions, lighting changes, image quality, and scale variations. The National Institute of Standards and Technology (NIST) [23] recently evaluated the effectiveness of facial recognition algorithms both before and after the COVID-19 pandemic. NIST researchers modified pre-pandemic facial recognition algorithms to handle masked faces but found that they still did not meet the desired performance standards.

Despite significant advancements in deep learning, facial recognition remains challenging when faces are partially obscured. A typical facial recognition pipeline involves preprocessing raw images, detecting facial landmarks, aligning faces, extracting features, and classifying them [4]. Deep learning networks in facial recognition aim to represent complex, high-dimensional image information as low-dimensional feature vectors [5]. A typical deep convolutional neural network (DCNN) for facial recognition consists of convolutional layers, normalization, pooling layers, and fully connected layers [4]. Processing frame-by-frame image data using deep learning is computationally heavy regarding facial recognition [24].

The study by Anwar and Raychowdhuryh [25] addresses the challenge faced by current facial recognition systems in identifying individuals wearing masks The open-source face-masking tool MaskTheFace is proposed in this study, and as a result, a sizable collection of masked faces is generated. This tool applies masks to faces in images by recognizing key facial landmarks and adjusting the mask accordingly. By utilizing MaskTheFace, it is possible to enhance the accuracy of an existing facial recognition system through retraining. The retrained system, based on Facenet, showed a significant improvement in recognizing masked faces, with a 38% increase in the true positive rate. This tool offers support for five distinct mask types, and users have the flexibility to incorporate custom masks as well. Furthermore, it can also be utilized to transform any pre-existing face set into a masked-face dataset. The retrained system's accuracy was also evaluated using a custom real dataset, MFR2, which yielded comparable accuracy results [25].

While MFR remains an important task, it is still challenging because of the lack of a significant large dataset. Geng et al. [26] introduced IAMGAN, a novel identity-aware mask generative adversarial network, to generate synthetic masked face images from unmasked images using the MFSR dataset. This dataset consists of two parts. "The first part contains 9,742 web-collected masked face images with manually labelled mask region segmentation annotation, and the second part contains 11,615 images collected from 1,004 identities, in which 704 are real-world collected and the rest 300 identities are obtained from Internet". The MFSR dataset presents a challenging benchmark due to its diverse range of poses, lighting conditions, facial expressions, and mask types. To address the significant intra-class variation between full and masked faces, this paper proposes a class center learning approach. For each class, two class centers are defined: one for full-face images and one for masked-face images. A domain-constrained ranking loss (DCR) is employed to guide the model towards learning distinct features for masked and full-face images, enabling it to effectively differentiate between multiple identities. The paper proposes IAMGAN and DCR to address data scarcity and enhance the discriminative capability of masked face recognition models, demonstrating that their combination significantly improves performance and achieves state-of-the-art results on the new MFSR dataset.

Mandal et al. [27] proposed a framework based on the ResNet-50 architecture for identifying individuals wearing masks. The authors employed transfer learning to adapt a pre-trained ResNet-50 model for masked face recognition. The model was further refined through architectural modifications and hyperparameter tuning using unmasked images of the same individuals. The RMFRD (Real-world Masked Face Recognition Dataset) was used for this study. Domain adaptation techniques were used, treating unmasked faces as the source domain and masked faces as the target domain. The study evaluated two training scenarios: training exclusively on the source domain and training on both source and target domains. To enhance accuracy, the researchers experimented with various hyperparameter configurations Notably, the change in optimizer from Stochastic Gradient Descent (SGD) for the unmasked dataset to Adam for the masked dataset yielded the most favorable results. Specifically, they achieved an accuracy of 89% on their RMFRD dataset for unmasked faces, while the accuracy dropped to 47% for the masked face dataset.

Hariri [28] addressed the issue of the masked face recognition process and proposed a robust method based on discarding masked regions and using a deep convolutional neural network (CNN) that has already been trained to extract the best features from the unmasked face regions mostly eyes and forehead regions. The proposed method leverages a combination of deep learning techniques and a Bag-of-Features (BoF) paradigm to improve recognition accuracy. The approach proceeds with the exclusion of the occluded areas of the face hence considering only the regions that can be seen for instance the eyes and forehead. In the current work, features are extracted using a VGG-16 CNN which has been pretrained, from the last convolutional layer, the feature maps are then used in building a quantized representation using the BoF model. This quantized representation guarantees that the feature is light weighted, hence, one can be able to classify it using a Multilayer Perceptron (MLP). This was a more effective representation compared with fully connected layers in CNN's. The method is tested on the Real-World-Masked-Face-Dataset (RMFRD), achieving a high recognition rate of 91.3% under certain conditions, demonstrating its effectiveness in real-world applications.

One significant contribution to this field is the study by Li et al. [29], which proposed a combined cropping and attention-based approach for improving MFR accuracy. To overcome the occlusion problem, this approach works on the part of the face which is exposed when a mask is worn especially the eyes, which are slightly masked. The authors proposed a new technique that incorporates cropping and a technique called CBAM, (Convolutional Block Attention Module), deep learning technique that aims at improving feature extraction through attention to the relevant parts of an image. The cropping-based approach de-clutters the method of occlusion detection because it actually erases the masked area of the face of a person. CBAM complements this by applying attention mechanisms that prioritize the features from the unmasked regions, particularly around the eyes, thereby improving the network's focus on the most discriminative parts of the face. This method was tested on several datasets, including the Simulated Masked Face Recognition Dataset (SMFRD) and the AR dataset, and demonstrated substantial improvements in recognition performance, especially in challenging scenarios where masked faces were used for training to recognize unmasked faces, and vice versa. Compared to existing state-of-the-art methods, this approach showed a remarkable increase in accuracy, with gains of up to 18.5% in certain cases.

The study by Zhao et al. [30] introduces a novel Consistent Sub-Decision Network aimed at enhancing the accuracy of low-quality masked face recognition. The proposed method was to prioritize upper facial features, especially when they are not obscured by masks. This approach focuses on the inherent challenge of low-quality samples generated through simulation methods, where masks cause negative occlusions, leading to ambiguous or missing facial features. To address this, the authors propose an online consistency assessment structure that generates sub-decisions corresponding to different facial regions. These sub-decisions are then constrained using weighted bidirectional KL divergence, allowing the network to focus on unoccluded upper facial regions, thereby enhancing the extraction of discriminative features.

Al-Rammahi's [31] study introduced a face mask recognition system that uses MobileNetV2 and an optimization function to improve detection accuracy and efficiency. MobileNetV2, is a CNN architecture which known for less computation requirement for deep learning, hence appropriate for mobile and embedded systems. The model was trained with a database containing 3832 images where half of the images contained masked faces while the other half contained non-masked face images. Some measures were adopted to effectively handle the data including scaling and alteration to increase the robustness of the model. Adopting MobileNetV2 coupled with varying learning rates and data enhancement techniques resulted to a reasonably accurate one with the final classification accuracy standing at 99. 21 %. According to the analysis done by Al-Rammahi on MobileNetV2, the author points that if properly optimized, this model works best in detecting face masks. This work adds to the research on facial recognition during COVID-19 and offers a practical solution for ensuring public safety where masks are required.

Kocacinar et al., [32] extends this area of study with a new lightweight, real-time CNN based Masked Face Recognition system that is designed for mobile environments. The study addresses the gap in the face recognition technologies since the technologies should perform well even when only a part of the face is exposed because of the masks. The main and equally important objectives are to know whether a person wears a mask correctly, incorrectly, or at all; the second goal is to recognize the person covered with a mask. A key innovation in this research is the development of the MadFaRe dataset, which includes over 151,000 images classified into three categories: observed people complied fully with mask wearing, partly complied with it, and completely did not follow the rules. This dataset proved quite useful while training and fine-tuning CNN models to be used in the study especially when large datasets might not be easily available. MobileNet was employed by the authors on the idea that it was developed as a shallow deep learning model fine-tuned for mobile platforms. This model was validated to an accuracy of 90 %. This research also expands the use of the eye-region detection when most regions on the face are obscured by masks. This approach when combined with other methods like SRGAN used in image enhancement got an 82%accuracy thus showing a promising result. undefined Such enhancements further attest the sustainability and utilitarianism of the system in many practical uses such as security and safety or physical access to some areas.

Recently, Hao et al. [33] present a new method named as the Face Feature Rectification Network (FFR-Net) for face recognition in different circumstances. The primary innovation introduced by FFR-Net is brought by its capability to rectify features obtained from faces using masks or no mask at all so that the resulting features are coherent and discriminative in the feature space. It also includes rectification blocks which are RecBlocks where characteristics are altered in both space and channel domains to realign masked face features with their mask-free counterparts. As highlighted earlier in the evaluation of the recognition algorithms, alignment of the FLM with the SRM is crucial to ensure that high recognition accuracy is achieved under different conditions. The system employs face identification with the use of the SENet version for rectification processes. The authors validate the performance of FFR-Net with the tested LFW and MegaFace benchmarks demonstrating its advantage in comparison with current algorithms. Notably, while masks obscure the faces' features, FFR-Net achieved tremendous improvements in detecting faces with masks while at the same time offering a high degree of accuracy in detecting faces not wearing masks The study's experiments showed that the unified framework outperforms other approaches by achieving a balance between masked and mask-free recognition tasks, with minimal computational overhead.

Making use of facial recognition systems during the COVID-19 outbreak, Qi et al. [34] outlined a detailed approach to overcome the significant challenges that Masks pose to Facial recognition systems resulting from the covering of most of the face parts including the nose and mouth. The approaches are expected to minimize the differences in performance in masked and unmasked face recognition tasks in the ICCV2021 Masked Face Recognition (MFR) competition, by simply proposing modifications in the network design, data handling, and training methodologies. The current study also gives much attention to the problem of overfitting through training models only on masked face images to produce lower standard face recognition. To address this problem, the authors limited the proportion of the concealed images in the training set to be 10% of the total quantity in striving to balance both goals. The structure is built on the ArcFace platform using the ResNet as the framework that has undergone different improvements which include the stem unit inspired from YOLOv5 focus layer, regularization by DropBlock, as well as YOLO5Face for alignment. The authors demonstrate in their studies that these approaches improve the model's performance significantly in both tasks and the results obtained satisfy the criteria of the MFR challenge. The study's findings emphasize the importance of a balanced approach to training and network design in the context of masked face recognition, ensuring that models do not compromise their ability to accurately recognize faces in standard conditions.

To improve the fairness in masked face recognition, Yu et al. [35] propose a new algorithm. The primary concern of this study is in designing a masked face recognition system – a technology that is intended to reduce the effects of racism while enhancing the system's efficiency and effectiveness. The writers also point out that traditional facial recognition system has been known to work poorly when it comes to detecting certain races with the East Asians being particularly affected when their faces are hidden. Thus, to resolve this problem, the research employs different strategies including enhancement of mask efficiency, re-sampling of data, and introduction of an asymmetric arc-loss function. Masks need to be enhanced for developing a better collection of masks face database, since such data is rather scarce. There is the procedure that allows selecting the same amount of faces for each ethnicity; during the procedure, the emphasis is made on increasing the number of Asians, for instance. This is important as it will reduce a scenario whereby the model may favor a certain group than others due to the nature of the data fed to it. The Asymmetric Arc-Loss function that is a mixture of ArcFace loss and Circle loss was designed to improve the recognition rates, with less bias. Indeed, testing the proposed approach on various datasets, including the MS1M dataset, the reduction in prejudice is significant, between Caucasian and East Asian people in particular, and the recognition accuracy is also very high. Hence, the study shows that if these methods are integrated, they could bring a better balanced and adaptive facial recognition with masks.

The study by Neto et al. [36] critically evaluates several state-of-the-art MFR and OFR models to determine their effectiveness across both masked and other occluded face recognition tasks. The authors highlight that while MFR models have been specifically optimized to handle the occlusions caused by masks, the underlying principles and techniques could potentially benefit OFR, which deals with more varied and unpredictable occlusions. To test this hypothesis, the study employed a variety of occluded and masked face datasets, such as LFW and Occ-LFW, assessing the performance of MFR models like FocusFace and KD (Knowledge Distillation) when applied to general occluded face recognition tasks.

Azouji et al. [37] developed EfficientMask-Net, a lightweight, real-time face authentication system designed specifically for environments with limited computational resources, such as mobile devices and embedded systems. EfficientMask-Net is notable for its dual approach to face mask recognition. It first identifies face mask-wearing conditions through a deep convolutional neural network (CNN), followed by classification using a Large Margin Piecewise Linear (LMPL) classifier. The system distinguishes between correct face mask-wearing (CFM), incorrect face mask-wearing (IFM), and no face mask-wearing (NFM) in one classification scheme, and further refines these categories into uncovered chin, nose, and mouth in another. This granularity is crucial for accurately assessing mask compliance in real-world applications, such as public health monitoring and security systems.

The EfficientMask-Net utilizes EfficientNetB0 as the backbone for feature extraction, chosen for its balance between accuracy and computational efficiency, particularly on mobile devices. The LMPL classifier enhances the system's ability to distinguish between similar classes by optimizing decision boundaries through a unique loss function tailored for this task. Experimental results demonstrated that EfficientMask-Net achieved high accuracy rates of 99.53% and 99.64% in the two classification tasks, respectively, outperforming several other state-of-the-art models. In addition to mask detection, EfficientMask-Net also includes a face unmasking feature, which leverages a Generative Adversarial Network (GAN) to reconstruct the unmasked portions of the face, facilitating more accurate face authentication. This feature is particularly innovative as it allows the system to be integrated into existing biometric systems without requiring retraining on masked face datasets.

Damer et al. [38] conducted an extensive evaluation of the effect of both real and simulated masks on face recognition performance across multiple systems, including academic models like ArcFace, VGGFace, and SphereFace, as well as a commercial system, MegaMatcher. The study used a specifically curated database containing images with real masks, simulated masks, and no masks to assess the impact of these different conditions on face recognition accuracy. The results indicated that face masks, whether real or simulated, significantly degrade recognition performance. However, real masks have a more substantial negative impact compared to simulated ones. This discrepancy is particularly evident in how genuine face matches are increasingly misclassified as imposters, thereby reducing the separability between genuine and imposter scores, as shown by the Fisher Discriminant Ratio (FDR) and other performance metrics. Additionally, the study found that while simulated masks could provide a useful approximation, they fail to fully capture the variability and complexity of real masks, leading to over-optimistic performance estimates when used exclusively in testing.

The study by Doe et al. [39], presents a CNN-based approach specifically designed to address the challenges posed by face masks in recognition tasks. The authors created a face mask recognition system based on a deep CNN model, trained on a comprehensive dataset that included both masked and unmasked faces. This dataset was carefully selected to represent various mask types and face orientations, ensuring the model's effectiveness across different real-world situations. The CNN model used in this study features several convolutional layers followed by pooling layers, which gradually extract and reduce the size of features from the input images. These extracted features are then passed through fully connected layers to generate the final classification output, identifying whether a mask is present and, if so, recognizing the individual wearing the mask. The model was refined using transfer learning techniques, which involved utilizing pre-trained models on large-scale face recognition datasets. This approach significantly enhanced its performance on the masked face dataset. The evaluation results showed that the CNN model achieved high accuracy in both mask detection and recognizing masked individuals, with reported accuracy exceeding 95%. his level of performance highlights the effectiveness of deep learning methods in addressing the new challenges introduced by the pandemic.

The study by Wang et al. [40] proposes an improved face recognition model specifically designed to enhance recognition accuracy for masked faces. The study presents a system built on the ConvNeXt-T architecture, augmented with an Efficient Channel Attention (ECA) mechanism to enhance the extraction of distinctive features from the visible, unmasked parts of the face. The key innovation of this research is the incorporation of the attention mechanism, enabling the model to concentrate on the most informative facial features, especially when significant portions are covered by masks. The ECA mechanism is employed to emphasize crucial features without adding complexity to the model, allowing it to sustain high accuracy even under challenging conditions, like fluctuating brightness and contrast levels. This attention-based method overcomes the shortcomings of traditional face recognition systems, which often fail to accurately identify individuals when masks obscure significant parts of the face. To validate the effectiveness of the proposed model, the authors created a dataset containing real images of masked faces, augmented to simulate various challenging conditions. The model achieved an impressive accuracy rate of 99.76% in recognizing masked faces, demonstrating its robustness and potential applicability in real-world scenarios where mask-wearing is prevalent.

Table 1: Summary of the related works

| Method Used | Dataset | Key Findings | Limitations |
|---|---|---|---|
| MaskTheFace [25] | MFR2 (Custom real dataset) | Improved accuracy with a 38% increase in true positive rate. | Limited dataset size; |
| IAMGAN (Identity-aware mask GAN) with Class Center Learning) [26] | MFSR dataset (web-collected and real-world images) | Significant improvement in MFR performance using domain-constrained ranking loss (DCR) with state-of-the-art results. | Limited to MFSR dataset; more testing needed on larger, real-world datasets. |
| ResNet-50 with transfer learning and domain adaptation [27] | RMFRD (Real-world Masked Face Recognition Dataset) | Achieved 89% accuracy for unmasked faces, but only 47% for masked faces, highlighting the need for domain adaptation. | Drop in accuracy for masked faces; further refinement of domain adaptation techniques is needed. |
| VGG-16 CNN with Bag-of-Features paradigm [28] | RMFRD | Achieved 91.3% recognition accuracy by discarding masked regions and focusing on eyes and forehead. | Only effective when masks do not cover critical parts of the face like the eyes or forehead. |
| Cropping-based approach with CBAM (Convolutional Block Attention Module) [29] | SMFRD, AR dataset | Significant improvement in recognition performance with up to 18.5% increase in accuracy by focusing on unmasked regions. | May not generalize to scenarios where masks cover most of the face, including the eyes. |
| Consistent Sub-Decision Network with KL divergence [30] | Custom low-quality masked face dataset | Enhanced accuracy in low-quality masked face recognition by prioritizing unmasked facial features. | Limited by low-quality data simulations; more testing needed on higher-quality real-world images. |
| MobileNetV2 with optimization functions [31] | Custom database (3832 images) | Achieved 99.21% accuracy in detecting masked faces using MobileNetV2 optimized for mobile/embedded systems. | Focused on smaller, less complex datasets; real-world testing needed. |
| CNN-based Masked Face Recognition system (MobileNet) [32] | MadFaRe dataset (151,000+ images) | Achieved 90% accuracy; focused on recognizing individuals with masks and evaluating compliance in mask-wearing. | Dataset limited to compliance assessment, needs broader facial recognition testing. |
| FFR-Net (Face Feature Rectification Network) with RecBlocks [33] | LFW, MegaFace benchmarks | High accuracy in masked and unmasked face detection by aligning masked face features with unmasked counterparts. | Complex model architecture, increased computational overhead. |

| | | | |
|---|---|---|---|
| ArcFace with ResNet, regularization by DropBlock [34] | Custom masked face dataset | Improved accuracy through balanced masked/unmasked training; stem unit inspired from YOLOv5 focus layer. | Focused on network architecture, limited testing on larger, more varied datasets. |
| Asymmetric Arc-Loss function with enhanced mask efficiency [35] | MS1M dataset | Reduced bias in masked face recognition for East Asian faces, with increased fairness across ethnic groups. | Limited to testing ethnic bias; further testing on other minority groups is needed. |
| Knowledge Distillation (KD) and FocusFace [36] | LFW, Occ-LFW | MFR models can be adapted for general occluded face recognition, with promising results using KD and FocusFace. | Limited to small datasets; more testing required on large-scale occlusion cases. |
| EfficientMask-Net with Large Margin Piecewise Linear (LMPL) [37] | Custom masked face dataset | Achieved high accuracy (99.53%) in distinguishing correct/incorrect mask-wearing with a lightweight, real-time system. | Focused on mask-wearing detection, limited to a specific classification task. |
| Evaluation of real vs. simulated masks on face recognition [38] | Custom dataset (real and simulated masks) | Face masks degrade recognition performance, especially real masks; simulated masks overestimate system performance. | Simulated masks do not fully represent the complexity of real masks. |
| CNN-based mask recognition model with transfer learning [39] | Custom masked and unmasked face dataset | High accuracy (95%) in recognizing both masked and unmasked faces, using a deep CNN model and transfer learning. | Limited to a specific dataset; model may not generalize to more complex environments. |
| ConvNeXt-T with Efficient Channel Attention (ECA) [40] | Custom masked face dataset with augmented conditions | Achieved 99.76% accuracy in recognizing masked faces by focusing on critical facial features using ECA. | Limited testing on real-world datasets; primarily tested in controlled environments. |

The current state of masked face recognition (MFR) technologies, as indicated in the reviewed literature, showcases significant advancements in handling the challenges posed by occluded facial features. However, several notable limitations persist that underpin the necessity for the presented research:

- Data Limitations: Many studies rely on limited datasets, which can hinder generalization and performance evaluation.
- Mask Variety: Existing datasets often lack sufficient diversity in mask types, materials, and wearing styles.
- Occlusion Levels: The degree of occlusion caused by masks varies, making it difficult to develop models that are robust to all scenarios.
- Real-World Conditions: Evaluating performance in real-world environments with varying lighting, pose, and facial expressions is crucial but often challenging.
- Ethical Considerations: Privacy concerns and potential biases in facial recognition algorithms need to be addressed

# 3 Materials and methods

This work systematically reviews the explosive growth in the literature on masked face recognition, focusing on works between the years 2018 and 2024. Searches were conducted in the Scopus database using the following query: TITLE-ABS-KEY (“masked face recognition”) OR TITLE-ABS-KEY (“face mask recognition”). The search terms have been selected in such a manner that they will help to obtain only those articles that directly address the technological challenges and improvements in face recognition technology in the context of mask-wearing, which is gaining great momentum in regard to the COVID-19 pandemic. Several filters were placed to refine the dataset. The review will be restricted to peer-reviewed journal articles, conference papers, and book chapters that are in the English language and were published from 2018 through 2024. Non-research articles reporting surveys, reviews, editorials, books, letters, or opinions are generally excluded. Subject areas of relevance to computer science and engineering restrict the topic further to ensure the review scope is pertinent and relevant to technological developments in this arena.

After collecting the initial data, duplicate records were deleted to further clean the dataset. The final set of articles was exported to a CSV file for subsequent analysis through a bibliometric method. Accordingly, this was performed using VOSviewer version 1.6.19 and Biblioshiny. These interfaces allow the extraction of patterns regarding publication trends, co-authorship networks, and thematic concentrations about the scientific research field of masked face recognition. As Figure 1 shows, this structured approach will make the methodology transparent and reproducible; thus, the development of the landscape concerning masked face recognition research will be clearly visualized.

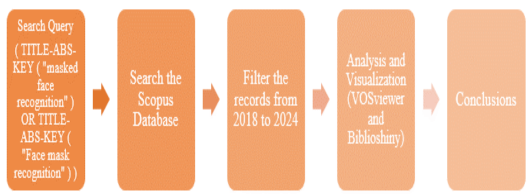


Figure 1: Methodology phases in masked face recognition research (2018–2024), showing the systematic process of data collection and analysis.

# 4 Results

## 4.1 Annual scientific production

Figure 2 shows the number of “masked face recognition” articles from 2018 to 2024. In the earlier years, specifically, from 2018 to around 2020, the focus on masked face recognition in the scientific community appears minimal, as evidenced by the low number of articles. However, a notable surge began in 2020, peaking around 2022. This heightened interest during this period might be attributed to global events like the COVID-19 pandemic, which popularized the use of face masks and underscored the necessity for advancements in face recognition technologies compatible with masks. Post-peak in 2022, there's a discernible decline in articles through 2024. This downturn could stem from various reasons: perhaps the prior surge yielded sufficient solutions to the challenges of masked face recognition, a potential reduction in the global prevalence of mask-wearing, or the emergence of other pressing research areas that diverted scholarly attention away from this topic.

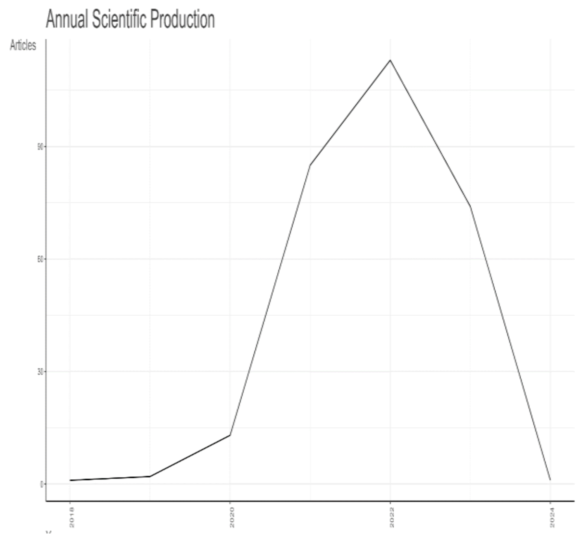


Figure 2: Annual scientific production in masked face recognition (2018–2024), highlighting a surge during the COVID-19 pandemic and a decline afterward.

## 4.2 Most significant authors

Among the most prominent authors in the research field, BOUTROS F leads with a contribution of 10 articles. Following closely is DAMER N with 9 articles. The authors WANG X and WANG Z have each contributed 7 articles, marking their significance in the domain. KIRCHBUCHNER F, WANG Y, and ZHANG Y each have 6 publications to their names. The list is rounded off with CARDOSO JS, KUIJPER A, and LI Y, each having contributed 5 articles. This roster of authors represents key contributors and influencers in the domain, based on their publication count.

## 4.3 Most relevant sources and affiliations

Figure 3 outlines the most relevant sources about the field masked face recognition. "Lecture Notes in Networks and Systems" stands out as the primary source, with a contribution of 12 documents. Next in line is "Proceedings of SPIE - The International Society for Optical Engineering," contributing 10 documents. This is closely followed by "Proceedings of the IEEE International

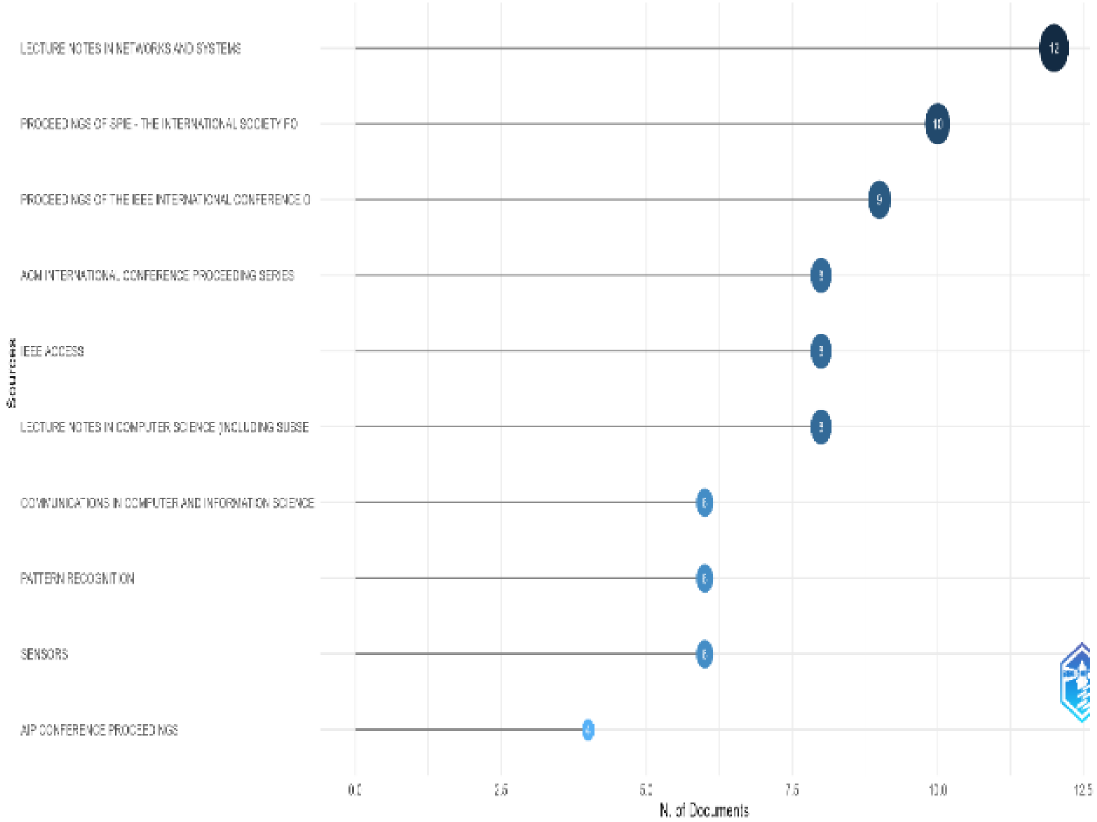


Figure 3: Top 10 sources in masked face recognition research (2018–2024).

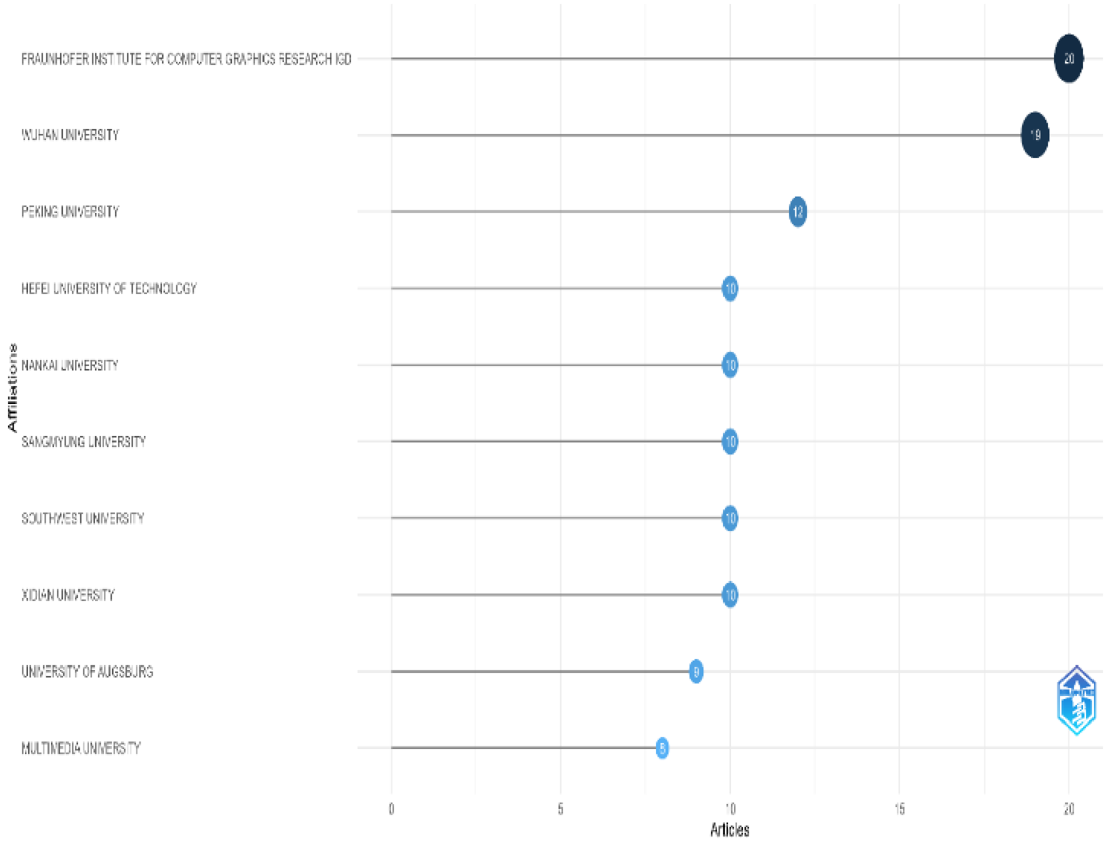


Figure 4: Significant affiliations in masked face recognition (2018–2024).

Conference on Computer Vision," which has contributed 9 documents. Further, "ACM International Conference Proceeding Series," "IEEE Access," "Lecture Notes in Computer Science (including its subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)," and "Communications in Computer and Information Science" have each made a notable impact, each offering 8 documents to the study. The sources "Pattern Recognition" and "Sensors" are also relevant, each with 6 documents. The list is concluded by "AIP Conference Proceedings," which has contributed 4 documents. These sources represent the pivotal publications and platforms providing significant information and studies in the domain, based on their document count.

Figure 4 showcases the most relevant affiliations in terms of their contributions to the domain. The "Fraunhofer Institute for Computer Graphics Research IGD" leads the list with a prominent contribution of 20 articles. This is closely followed by "Wuhan University," which has contributed 19 articles. Several institutions have made significant contributions of 10 articles each, including "Peking University," "Hefei University of Technology," "Nankai University," "Sangmyung University," "Southwest University," and "Xidian University." The "University of Augsburg" has also made a noteworthy impact with a contribution of 9 articles. Lastly, "Multimedia University" is represented with 8 articles. These affiliations are pivotal in advancing research and knowledge in the field, as evidenced by the number of their publications.

## 4.4 Three Field Plot of keyword, author and source

Figure 5 illustrates a three-field plot that delineates the intricate relationships among specific keywords, authors, and the sources of their publications. Within the realm of keywords, prominent terms like "Face Detection," "Deep Learning," "COVID-19," and "Computer Vision" emerge. These topics have seen contributions from notable authors such as li y, wang y, pinto jr, and sequeira af, among others. Delving into the sources, these scholars have predominantly published their work in esteemed journals and conferences. Some of the notable ones include the "Dammer Lecture Notes in Informatics (LNI) – Proceedings – Series of the Gesellschaft für Informatik (GI)," the "2021 IEEE International Joint Conference on Biometrics (IJCB 2021)," and the "IEEE Access." In essence, the plot serves as a visual representation of the synergy between keywords, contributing authors, and the platforms that house their research, offering a holistic view of the academic landscape in the depicted domain.

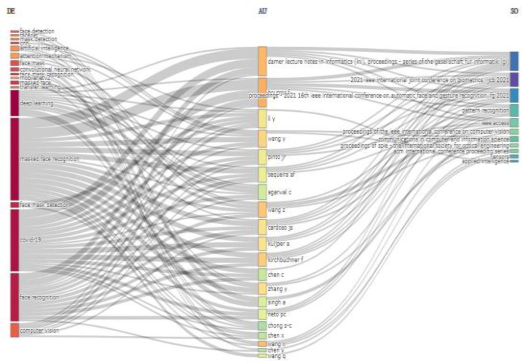

Figure 5: Three-field plot (2018–2024) showing connections between keywords, authors, and sources in masked face recognition research.

## 4.5 Trend topics

Figure 6 provides a visual representation of trending topics over the year 2022. It emphasizes the term frequency of various subjects, illustrated through the size of the circles. Topics such as "face recognition performance" have witnessed a considerable surge in popularity, as evident from its notably larger circle size, suggesting a term frequency nearing 200. In contrast, topics like "embeddings," "face mask recognition," "detection system," and "face recognition" have also seen traction, though with a term frequency closer to 50. More intermediate frequencies are observed for terms such as "deep learning," "face masks," "coronavirus," and "machine learning." The themes of face recognition, machine learning, and health-related topics like coronavirus have been predominant in 2022's discourse.

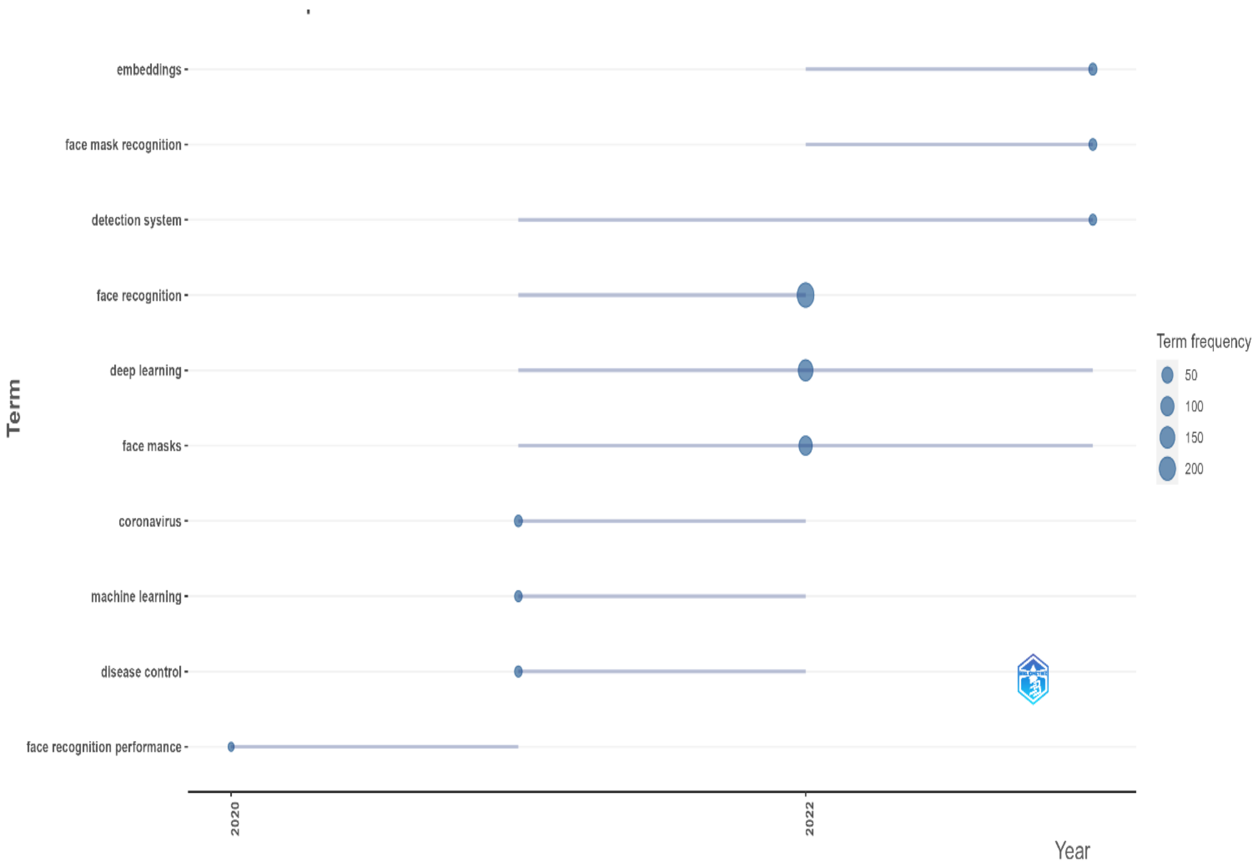


Figure 6: Trending topics in masked face recognition (2018–2024)

## 4.6 Thematic map

Figure 7 organizes various themes according to their development and centrality. Themes in the "Niche" category, such as "article," "coronavirus disease 2019," "pandemics," "collaborative environments," "contactless methods," and "exploratory studies," demonstrate substantial development but are not centrally dominant in the discourse. Central to the main conversation are the "Motor Themes" which include "masked face recognition," "face recognition systems," and "wear of materials." These themes are both highly developed and central. Conversely, "Emerging or Declining Themes" like "human," "humans," and "pandemic" may be gaining momentum or phasing out, marked by their position at the lower end of development. Finally, serving as the bedrock of the conversation are the "Basic Themes." These include "face recognition," "face masks," "deep learning," "COVID-19," "facial recognition," and "learning systems," which, while central, aren't as densely elaborated upon. Overall, the graph provides insights into the prominence and development of themes within masked face recognition.

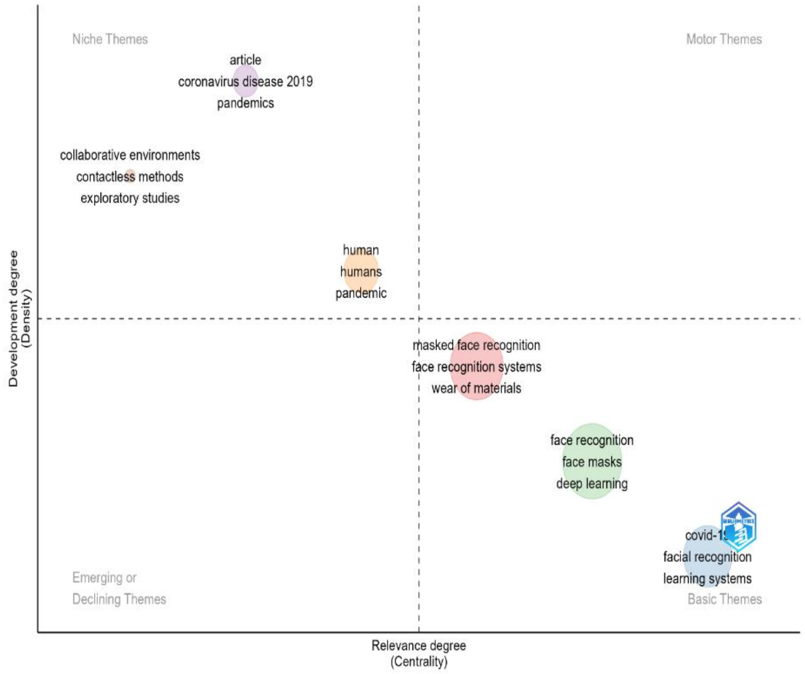


Figure 7: Thematic map in masked face recognition (2018–2024), categorizing motor and emerging themes in the field**.**


Figure 8: Tree map of key themes in masked face recognition research (2018–2024).

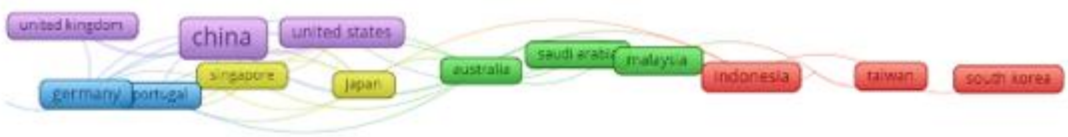


Figure 9: Country co-authorship network (2018–2024), showing global collaborations in masked face recognition, with key players.

## 4.7 Tree map

Figure 8 is a tree map that delineates various themes pertinent to facial recognition technology, especially in the context of the COVID-19 pandemic. Each block's size corresponds to its relative prominence, with percentages offering a clear measure of its importance. "Face recognition" stands out as the most dominant theme, covering 15% of the tree map, highlighting its centrality in the overall discourse. "Deep learning" follows closely, occupying 10%, underscoring its foundational role in contemporary facial recognition applications. Other notable mentions include another segment labelled "Face recognition" at 7%, and "Covid-19" at 5%, emphasizing the pandemic's significant influence on this technology's progression and adaptation.

## 4.8 Country co-authorship analysis

Figure 9 illustrates a country co-authorship analysis in the domain of masked face recognition. It provides a network of countries that have been collaborating on research topics related to masked face recognition. The thickness and number of lines connecting each country depict the intensity and frequency of collaborations.

Central to the graph are major players like China, the United States, and Singapore. China appears to have substantial collaborative ties with the United States, Singapore, and Japan. The United States is also interlinked with countries like Australia and Japan. In the European sector, the United Kingdom established connections with Germany and Portugal. The eastern hemisphere shows active research collaborations among countries such as South Korea, Taiwan, Indonesia, and Malaysia, with Saudi Arabia serving as a notable collaborator in the Middle East. Overall, the visualization signifies a global cooperative effort in advancing masked face recognition research, with Asian countries being particularly active in this arena.

## 4.9 Co-occurrence of keywords

Figure 10 illustrates the co-occurrence of keywords in the masked face recognition. The green group illustrates the relationship between "machine learning", “face mask recognition”, “learning algorithms” and face mask detection. It recommends giving much emphasis on the methodologies applied in face recognition when masks are worn. The red cluster shows the tools and methods involved in recognition process. Various terms like “neural networks”, "convolutional neural networks", "image segmentation, image enhancement," and "recognition models” There is no doubt that advanced computational methods and facial recognition technologies have come together. A blue cluster next to it covers the technical basis of face recognition. In this section, we notice "convolution", “transfer learning”, “openCV”, and particular model names such as ‘vgg16’ and ’mobilenetv2’. In addition, COVID-19 face images and associated terms such as “viruses” or” public places appear in the vicinity. This highlights the importance of masked face recognition in the current situation with COVID-19. Last, there is a discussion of practical uses and consequences for this technology in the real world. Masked face recognition is associated with broader societal impacts and applications of “biometrics”, “contactless,” “security systems,” and to the process or act of verifying identity. In general, the visualisation portrays all aspects of masked face recognition from technical approaches to social consequences especially after major world challenges like COVID

## 4.10 Bibliographic coupling with sources

Masked face recognition bibliographic coupling in figure 11 introduces a novel perspective on the inter-connectivity and collaborative nature of studies in this area. The global pandemic has led to an increased use of face masks since the same time that academic interest in adapting facial recognition systems also grew as a way for them to recognize individuals even when their faces were covered. Major sources like the IEEE and ACM, which are some of the best organizations when it comes to electrical engineering and computer science have widely published research about this topic. For instance, "IEEE Access" has been the forerunner in publishing multidisciplinary open-access articles on masked face recognition. Also, the phrase “pattern recognition” used in this context implies concentrating on finding patterns among cipher faces where machine learning techniques are frequently implemented. The dense interlinking between these terms and sources underscores the synergy among researchers and highlights the collaborative efforts to tackle the challenges posed by masked face recognition.

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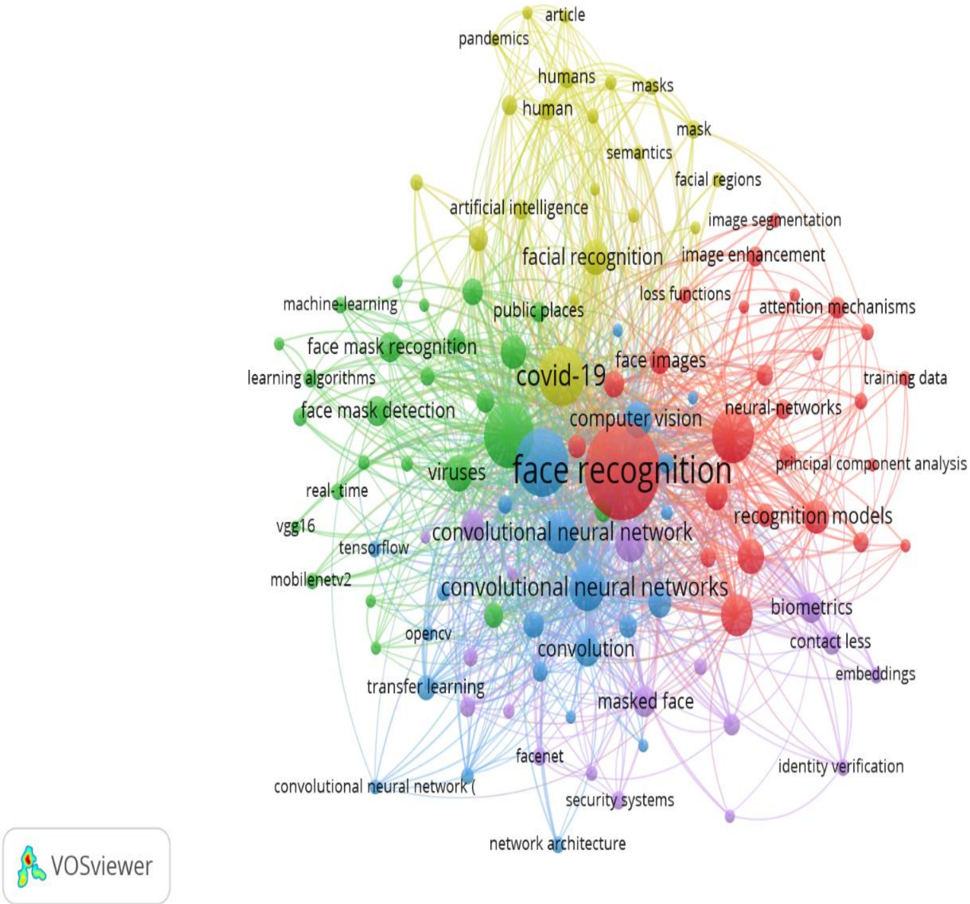


Figure 10: Keyword co-occurrence network (2018–2024), highlighting technical and societal connections in masked face recognition research.

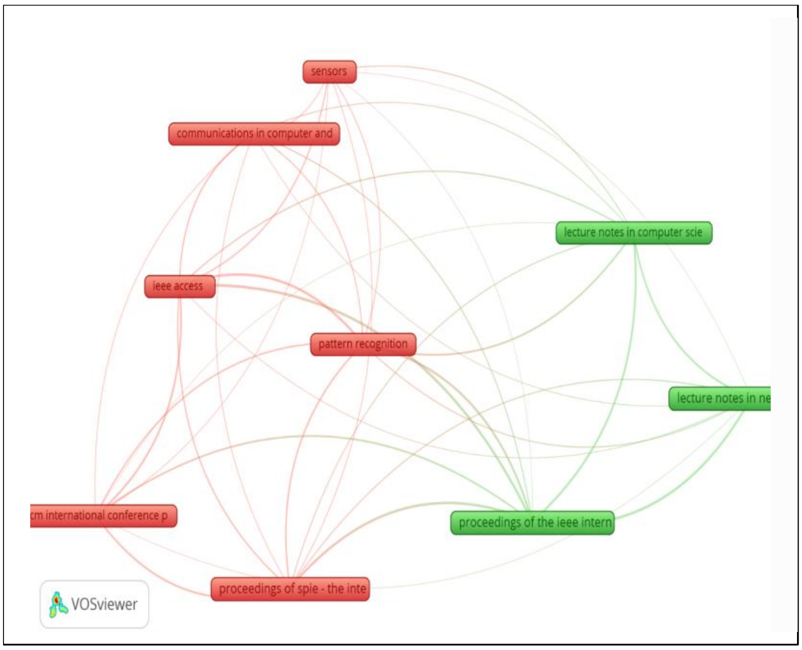


Figure 11: Bibliographic coupling with sources (2018–2024), showing interconnectivity among leading publications.

## 5 Discussion

In recent years, masked face recognition has undergone a dramatic shift in its focused attention, especially amidst global health challenges that reached their crescendo with the COVID-19 pandemic. Contrary to related works in the past, which had their core focus on traditional face recognition technologies, this study highlights how fast the evolution of research attention has been in addressing the challenges brought forth by occlusion due to masks. One of the more striking points of variance between this and past works is that the trends in masked face recognition represent an emergent topic after 2020, while previously, most research has dealt with facial recognition when the face is unmasked. This shift reflects the degree to which there is a technological advancement in adapting existing recognition algorithms to handle partial occlusion complexity, reflected by deep learning and CNNs now playing a salient role in this domain. In this paper, a first view from a bibliometric perspective has been given on not only the surge of interest in masked face recognition but also the key methods and authors driving this shift.

The bibliometric analysis also brings to light emerging topics related to new technological developments. The emphasis on the deep learning approach, for instance, with the incorporation of transfer learning, together with CNN architectures such as VGG16 and MobileNetV2, reflects how researchers are fine-tuning and applying such tools in order to arrive at higher recognition accuracy even when occluded. Previous works were focused on full-face recognition systems that, while applied on mask-wearing populations, received many limitations. We also disclose how recent state-of-the-art works have now focused their research on mitigating these limitations by adopting newer approaches such as face feature embeddings and face detection models that have been fine-tuned for mask-wearing faces. The emphasis on emerging technologies in this regard comprises a new direction of research which previous bibliometric analyses might have missed, especially those published prior to the pandemic.

Together with technological novelties, this paper discusses broader societal impacts in the post-COVID-19 context that encourage wider collaboration across global research institutions. Our country co-authorship analysis populated the international collaborations, especially between countries like China, the US, and Singapore that were severely affected by the pandemic and thus responded by making hefty investments in masked face recognition technologies. This contrasts with pre-pandemic-related studies, which have not focused on the role of events within society in shaping research collaborations. This rise from 2020 to 2022 reflects, above all, the urgent need felt for mask-compatible security systems and points to the fact that research has also been reactive to technologically driven demands and to the crisis which hit society.

The added value of this bibliometric study lies in the fact that it links the evolution of face recognition technologies directly with events arising from the pandemic, which reshaped research priorities within the area. It should indeed be the case that this study will provide insight into the consequences of recent global events for technological development and for interdisciplinary collaborations that is probably not captured by previous studies in quite as much detail. Moreover, the analysis of decreasing trends in 2023 and beyond offers a unique perspective on how this research area may settle down or shift again to meet new global challenges. The broader temporal and technological context, combined with focuses on societal impacts, makes this bibliometric study different from earlier works.

## 6 Future research directions

Future research on masked face recognition needs to surmount some critical technological, ethical, and policy challenges. Technologically, there is a need to improve the accuracy of the recognition system when the subjects are occluded-for example, by wearing a face mask-using a hybrid model leveraging both CNNs and transformers. Besides, the development of real-time and scalable applications for populated areas like airports and hospitals will definitely be inevitable. Other timely concerns would be generalization across diverse populations, as most of the systems developed so far have biases in identification against people from different ethnic backgrounds. Ethically, privacy and fairness shall always remain key considerations in any future study.

Approaches for maintaining privacy include federated learning and differential privacy that protect individual identity, while approaches for addressing bias involve more representative datasets and algorithmic decision-making transparency, especially in law enforcement and security. From the policy perspective, there is an urgent need for wider regulatory frameworks spelling out ethical uses of masked face recognition technologies in a balancing act between public safety and individual rights. Broad acceptance and ethical implementation will require interoperable global standards and deployment practices that are transparent enough to ensure public trust. The ability to address these challenges provide a guide to the responsible development and application of masked face recognition in the future.

## 7 Conclusion

The bibliometric analysis of masked face recognition offers a thorough picture of the research field by revealing its historical evolution, major achievements as well as repeated topics. Therefore, as a consequence of the requirements that COVID-19 pandemic imposed on people, this once marginal field became prevalent showing how science and world events are related in an intricate manner. The enormous production from 2020 to 20 suggests that the academic and technological fields responded swiftly to the challenges presented by common mask use. Well recognized authors and institutions have acted as lighthouses in this regard guiding the research while defining benchmarks for innovation, practice. I began by using an extensive keyword list, which allowed me to write about the domain's intricacies such as technological milestones, social implications and health issues. Secondly, the spirit of international collaboration in terms of country co-authorships represents how widespread is this problem called masked face identification and commitment from all parties that there should be a solution for it. Governments-scholar's partnership in tackling current technology concerns emphasizes the global village notion. In conclusion, this study has highlighted the importance of masked face recognition in an evolving world while also documenting its success and growth. The results of the performed research create a theoretical lens to process what happened in such an environment, how it is happening now and will develop further one day.

# References

[1] A. Dey and M. Ghosh, "A Novel Approach to Fuzzy-Based Facial Feature Extraction and Face Recognition," *Informatica*, vol. 43, no. 4, Art. no. 4, Jan. 2020, doi: https://doi.org/10.31449/inf.v43i4.2117.

[2] N. K. Ratha, V. M. Patel, and R. Chellappa, Eds., *Deep Learning-Based Face Analytics*. in Advances in Computer Vision and Pattern Recognition. Cham: Springer International Publishing, 2021. doi: 10.1007/978-3-030-74697-1.

[3] S. Cherian and B. Thomas, "MASKED FACE DETECTION: ADVANCEMENTS, CHALLENGES, AND RESEARCH DIRECTIONS," *Journal of Theoretical and Applied Information Technology*, vol. 101, no. 21, 2023, [Online]. Available: https://www.jatit.org/volumes/Vol101No21/4Vol101No21.pdf

[4] S. P. K. Wickrama Arachchilage and E. Izquierdo, "Deep-learned faces: a survey," *EURASIP Journal on Image and Video Processing*, vol. 2020, no. 1, p. 25, Jun. 2020, doi: https://doi.org/10.1186/s13640-020-00510-w.

[5] W. Ali, W. Tian, S. U. Din, D. Iradukunda, and A. A. Khan, "Classical and modern face recognition approaches: a complete review," *Multimed Tools Appl*, vol. 80, no. 3, pp. 4825–4880, Jan. 2021, doi: https://doi.org/10.1007/s11042-020-09850-1.

[6] D. Akingbesote, Y. Zhan, R. Maskeliūnas, and R. Damaševičius, "Improving Accuracy of Face Recognition in the Era of Mask-Wearing: An Evaluation of a Pareto-Optimized FaceNet Model with Data Preprocessing Techniques," *Algorithms*, vol. 16, no. 6, p. 292, Jun. 2023, doi: https://doi.org/10.3390/a16060292.

[7] M. Alexiou, I. P. Ktistakis, and G. Goodman, "Towards a Masked Face Recognition Algorithm: A Novel Rule Based Hybrid Algorithm," in *2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)*, 2021, pp. 1–6. doi: https://doi.org/10.1109/seeda-cecnsm53056.2021.9566244.

[8] B. Mukherjee, "Analysis of Global Research Trends in Coronaviruses: A Bibliometric Investigation," *JSCIRES*, vol. 9, no. 2, pp. 185–194, Jul. 2020, doi: https://doi.org/10.5530/jscires.9.2.22.

[9] C. Chen, R. Dubin, and M. C. Kim, "Emerging trends and new developments in regenerative medicine: a scientometric update (2000 – 2014)," *Expert Opinion on Biological Therapy*, vol. 14, no. 9, pp. 1295–1317, Sep. 2014, doi: https://doi.org/10.1517/14712598.2014.920813.

[10] S. Singh, A. Solkhe, and P. Gautam, "What do we know about Employee Productivity?: Insights from Bibliometric Analysis," *J Scientometric Res.*, vol. 11, no. 2, pp. 183–198, Sep. 2022, doi: https://doi.org/10.5530/jscires.11.2.20.

[11] M. A. Al Mamun, M. A. K. Azad, M. A. Al Mamun, and M. Boyle, "Review of flipped learning in engineering education: Scientific mapping and research horizon," *Educ Inf Technol*, vol. 27, no. 1, pp. 1261–1286, Jan. 2022, doi: https://doi.org/10.1007/s10639-021-10630-z.

[12] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct a bibliometric analysis: An overview and guidelines," *Journal of Business Research*, vol. 133, pp. 285–296, Sep. 2021, doi: https://doi.org/10.1016/j.jbusres.2021.04.070.

[13] B. Godin, "On the origins of bibliometrics," *Scientometrics*, vol. 68, no. 1, pp. 109–133, Jul. 2006, doi: https://doi.org/10.1007/s11192-006-0086-0.

[14] J. S. Barrot, "Trends in automated writing evaluation systems research for teaching, learning, and assessment: A bibliometric analysis," *Educ Inf Technol*, Aug. 2023, doi: https://doi.org/10.1007/s10639-023-12083-y.

[15] L. T. Dao, T. Tran, H. Van Le, G. N. Nguyen, and T. P. T. Trinh, "A bibliometric analysis of Research on

Education 4.0 during the 2017–2021 period," *Educ Inf Technol*, vol. 28, no. 3, pp. 2437–2453, Mar. 2023, doi: https://doi.org/10.1007/s10639-022-11211-4.

[16] L. Waltman, N. J. van Eck, and E. C. M. Noyons, "A unified approach to mapping and clustering of bibliometric networks," *Journal of Informetrics*, vol. 4, no. 4, pp. 629–635, Oct. 2010, doi: https://doi.org/10.1016/j.joi.2010.07.002.

[17] J. S. Racine, "Rstudio: A Platform-Independent Ide for R and Sweave," *Journal of Applied Econometrics*, vol. 27, no. 1, pp. 167–172, 2012, doi: https://doi.org/10.1002/jae.1278.

[18] E. Souza de Cursi, "Some Tips to Use R and RStudio," in *Uncertainty Quantification using R*, E. Souza de Cursi, Ed., in International Series in Operations Research & Management Science. , Cham: Springer International Publishing, 2023, pp. 1–108. doi: 10.1007/978-3-031-17785-9_1.

[19] F. J. Agbo, S. S. Oyelere, J. Suhonen, and M. Tukiainen, "Scientific production and thematic breakthroughs in smart learning environments: a bibliometric analysis," *Smart Learning Environments*, vol. 8, no. 1, p. 1, Jan. 2021, doi: https://doi.org/10.1186/s40561-020-00145-4.

[20] H. Ni, "Face Recognition Based on Deep Learning Under the Background of Big Data," *Informatica*, vol. 44, no. 4, Art. no. 4, Jan. 2021, doi: https://doi.org/10.31449/inf.v44i4.3390.

[21] M. Ibrahim, Md. I. A. Efat, S. M. Khaled, and M. Shoyaib, "Face verification with fully dynamic size blocks based on landmark detection," in *2014 International Conference on Informatics, Electronics & Vision (ICIEV)*, May 2014, pp. 1–5. doi: https://doi.org/10.1109/iciev.2014.6850737.

[22] M. Wang and W. Deng, "Deep face recognition: A survey," *Neurocomputing*, vol. 429, pp. 215–244, Mar. 2021, doi: https://doi.org/10.1016/j.neucom.2020.10.081.

[23] M. Ngan, P. Grother, and K. Hanaoka, "Ongoing Face Recognition Vendor Test (FRVT) part 6A:: face recognition accuracy with masks using pre-COVID-19 algorithms," National Institute of Standards and Technology, Gaithersburg, MD, NIST IR 8311, Jul. 2020. doi: https://doi.org/10.6028/nist.ir.8311.

[24] W. A. Fauzi, S. M. S. Nugroho, E. M. Yuniarno, W. Anggraeni, and M. H. Purnomo, "Multiple Face Tracking using Kalman and Hungarian Algorithm to Reduce Face Recognition Computational Cost," *JAREE*, vol. 5, no. 1, Apr. 2021, doi: https://doi.org/10.12962/jaree.v5i1.191.

[25] A. Anwar and A. Raychowdhury, "Masked Face Recognition for Secure Authentication," Aug. 25, 2020, *arXiv*: arXiv:2008.11104. doi: https://doi.org/10.48550/arXiv.2008.11104.

[26] M. Geng, P. Peng, Y. Huang, and Y. Tian, "Masked Face Recognition with Generative Data Augmentation and Domain Constrained Ranking," in *Proceedings of the 28th ACM International Conference on Multimedia*, Seattle WA USA: ACM, Oct. 2020, pp. 2246–2254. doi: https://doi.org/10.1145/3394171.3413723.

[27] B. Mandal, A. Okeukwu, and Y. Theis, "Masked Face Recognition using ResNet-50," 2021, doi: https://doi.org/10.48550/arXiv.2104.08997.

[28] W. Hariri, "Efficient masked face recognition method during the COVID-19 pandemic," *Signal, Image and Video Processing*, vol. 16, no. 3, pp. 605–612, Apr. 2022, doi: 10.1007/s11760-021-02050-w.

[29] Y. Li, K. Guo, Y. Lu, and L. Liu, "Cropping and attention based approach for masked face recognition," *Appl Intell*, vol. 51, no. 5, pp. 3012–3025, May 2021, doi: https://doi.org/10.1007/s10489-020-02100-9.

[30] W. Zhao, X. Zhu, H. Shi, X.-Y. Zhang, and Z. Lei, "Consistent Sub-Decision Network for Low-Quality Masked Face Recognition," *IEEE Signal Process. Lett.*, vol. 29, pp. 1147–1151, 2022, doi: https://doi.org/10.1109/lsp.2022.3170246.

[31] A. H. I. Al-Rammahi, "Face mask recognition system using MobileNetV2 with optimization function," *Applied Artificial Intelligence*, vol. 36, no. 1, p. 2145638, Dec. 2022, doi: https://doi.org/10.1080/08839514.2022.2145638.

[32] B. Kocacinar, B. Tas, F. P. Akbulut, C. Catal, and D. Mishra, "A Real-Time CNN-Based Lightweight Mobile Masked Face Recognition System," *IEEE Access*, vol. 10, pp. 63496–63507, 2022, doi: https://doi.org/10.1109/access.2022.3182055.

[33] S. Hao, C. Chen, Z. Chen, and K.-Y. K. Wong, "A Unified Framework for Masked and Mask-Free Face Recognition via Feature Rectification," Feb. 15, 2022, *arXiv*: arXiv:2202.07358. doi: https://doi.org/10.1109/icip46576.2022.9897292.

[34] D. Qi, K. Hu, W. Tan, Q. Yao, and J. Liu, "Balanced Masked and Standard Face Recognition," in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1497–1502. doi: https://doi.org/10.1109/iccvw54120.2021.00174.

[35] J. Yu, X. Hao, Z. Cui, P. He, and T. Liu, "Boosting Fairness for Masked Face Recognition," in *2021*

*IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1531–1540. doi: https://doi.org/10.1109/iccvw54120.2021.00178.

[36] P. C. Pedro Neto, J. R. Pinto, F. Boutros, N. Damer, A. F. Sequeira, and J. S. Cardoso, "Beyond Masks: On the Generalization of Masked Face Recognition Models to Occluded Face Recognition," *IEEE Access*, vol. 10, pp. 86222–86233, 2022, doi: https://doi.org/10.1109/access.2022.3199014.

[37] N. Azouji, A. Sami, and M. Taheri, "EfficientMask-Net for face authentication in the era of COVID-19 pandemic," *SIViP*, vol. 16, no. 7, pp. 1991–1999, Oct. 2022, doi: https://doi.org/10.1007/s11760-021-02050-w.

[38] N. Damer, F. Boutros, M. Süßmilch, F. Kirchbuchner, and A. Kuijper, "Extended evaluation of the effect of real and simulated masks on face recognition performance," *IET Biometrics*, vol. 10, no. 5, pp. 548–561, Sep. 2021, doi: https://doi.org/10.1049/bme2.12044.

[39] G. Kaur *et al.*, "Face mask recognition system using CNN model," *Neuroscience Informatics*, vol. 2, no. 3, p. 100035, Sep. 2022, doi: https://doi.org/10.1016/j.neuri.2021.100035.

[40] Y. Wang, Y. Li, and H. Zou, "Masked Face Recognition System Based on Attention Mechanism," *Information*, vol. 14, no. 2, Art. no. 2, Feb. 2023, doi: https://doi.org/10.3390/info14020087.