International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 10, October 2026)

Disaster Victim Identification System using Facial Recognition and Forensic Image Analysis

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***Abstract*—Disaster Victim Identification (DVI) is a critical forensic process used to establish the identity of individuals following disasters, accidents, criminal incidents, and other mass-fatality events. Conventional identification techniques such as DNA analysis, fingerprints, dental records, and radiological comparison can become difficult when remains are damaged, incomplete, or when ante-mortem reference information is un-available. Recent advances in computer vision, deep learning, facial reconstruction, and cross-domain image matching have introduced automated approaches for assisting forensic iden-tification. This paper presents a literature survey of existing methods relevant to a Disaster Victim Identification System using Facial Recognition and Forensic Image Analysis. Twenty selected studies are reviewed, covering deep metric learning, Siamese networks, generative adversarial networks, generative AI, skull-to-face matching, facial soft-tissue analysis, automatic landmark detection, 3-D shape matching, and computer-aided facial reconstruction. The reviewed studies demonstrate that deep learning can improve the speed and automation of forensic image analysis, while anatomical and soft-tissue information remains important for reliable facial reconstruction. However, challenges including limited paired skull-face datasets, cross-domain vari-ation, population-specific soft-tissue measurements, landmark annotation, reconstruction uncertainty, and the need for forensic validation remain. The survey identifies these limitations and highlights the potential for an integrated DVI system combining facial recognition, forensic image analysis, and reconstruction techniques.**

***Index Terms*—Disaster Victim Identification, forensic facial recognition, facial reconstruction, skull-to-face matching, deep learning, forensic image analysis, craniofacial identification, com-puter vision.**

I. Introduction

Disaster Victim Identification (DVI) involves the system-atic identification of deceased individuals following disasters, accidents, terrorist attacks, and other mass-fatality incidents. Identification is particularly challenging when remains are severely damaged or when conventional biometric evidence is unavailable. In such circumstances, forensic facial analysis and facial reconstruction can provide valuable investigative assistance.

Traditional forensic facial reconstruction relies substantially on anatomical knowledge, facial soft-tissue measurements, cranial landmarks, and expert interpretation. Although these methods can assist investigators in generating a facial approximation, they may require considerable time and specialist expertise. Sripoo [1] reviewed forensic facial reconstruction methods and highlighted the usefulness of computer-based reconstruction and facial superimposition in reducing the time associated with conventional approaches.

Recent research has increasingly incorporated artificial in-telligence and computer vision into forensic identification. Deep learning models can extract discriminative facial or cranial features, while generative models can synthesize fa-cial representations from skeletal information. Li *et al.* [2] introduced CR-GAN for automatic craniofacial reconstruction, demonstrating the potential of adversarial learning to gener-ate facial images from skull images. Similarly, Mohammed *et al.* [3] investigated a convolutional neural network-based approach for facial reconstruction from unidentified skulls.

For DVI applications, identification does not necessarily re-quire generating a complete facial reconstruction. Deep metric learning and cross-domain matching can instead determine whether a forensic image corresponds to an individual in an available database. Piotrowski *et al.* [4] developed a DVI system supported by a mobile application and applied deep metric learning for victim verification. More recent work has investigated Siamese networks, graph representations, optimal transport, and shared feature spaces for matching skull and facial images [5]–[8].

This paper surveys these developments with the objective of understanding existing techniques that can contribute to an automated DVI system using facial recognition and forensic image analysis. The review focuses on the methods, contri-butions, advantages, limitations, and research gaps identified across the selected literature.

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II. Review Of Existing Methods

A. Conventional and Computer-Aided Facial Reconstruction

Forensic facial reconstruction attempts to estimate the ap-pearance of an individual from skeletal remains. The process traditionally depends on anatomical landmarks and facial soft-tissue thickness values. Sripoo [1] observed that computer-based reconstruction can reduce the time and cost associated with traditional reconstruction and can be particularly useful during the initial stages of an investigation.

Wilkinson *et al.* [9] examined the standards used for cranio-facial identification and emphasized the importance of reliable and reproducible anatomical and anthropometrical measure-ments. Their review demonstrates that the quality of facial reconstruction depends not only on computational methods but also on the standards and datasets used to model the relationship between the skull and facial soft tissue.

Soft-tissue measurements are therefore an important com-ponent of reconstruction. Hona and Stephan [10] reviewed facial soft-tissue thickness data accumulated over more than a century and highlighted substantial variation among datasets. Koza´kova´ *et al.* [11] further demonstrated that head position can influence facial soft-tissue thickness measurements. Cos¸kun [12] compared 2-D and 3-D soft-tissue depth measure-ment methods and found that although statistically significant differences can occur, the practical differences between the methods can be small.

These studies indicate that anatomical and measurement variability must be considered when designing automated reconstruction systems.

B. Deep Learning for Facial Reconstruction

Deep learning has provided an alternative to manual recon-struction. CR-GAN, proposed by Li *et al.* [2], uses adversarial learning to synthesize facial images from skull images. The study demonstrated the potential of generative models for auto-mated craniofacial reconstruction and evaluated the generated faces using face recognition systems.

Mohammed *et al.* [3] proposed a deep-learning approach for reconstructing facial features from unidentified skull im-ages. Their approach demonstrates how convolutional neural networks can replace parts of the traditional reconstruction process. However, the authors also identified the lack of genuine paired skull-face forensic datasets as an important limitation.

Michael *et al.* [13] proposed Skull2Face, an anatomy-guided 3-D facial reconstruction system that combines deep learning with tissue-depth modelling. The approach attempts to produce a 3-D facial mesh while incorporating anatomical information. Nuthan *et al.* [14] similarly proposed an automated skull-to-face feature mapping system that performs preprocessing, landmark localization, and feature-to-region mapping to gen-erate an approximate facial representation.

Prasad and Singh [15] investigated generative AI models for forensic craniofacial reconstruction using 2-D X-ray repre-sentations. Their framework evaluates generative models such as CycleGAN and conditional GANs for translating between skull and facial domains. The generated faces were evaluated using image-quality measures including FID, IS, and SSIM.

These approaches show a progression from manually guided reconstruction toward automated generative systems. How-ever, generated facial images should be regarded as forensic approximations rather than guaranteed representations of an individual's actual appearance.

C. Cross-Domain Skull-to-Face Matching

An important challenge in forensic identification is the difference between the skull domain and the facial-image domain. A skull X-ray and a visible facial photograph have substantially different visual characteristics. Direct application of conventional face recognition models is therefore insufficient.

Prasad and Singh [5] investigated cross-domain identity rep-resentation using convolutional Siamese networks. Their work introduced a benchmark dataset containing paired skull X-ray and facial images and trained Siamese networks to learn a shared representation. This approach focuses on retrieving the corresponding face from a gallery rather than reconstructing the complete face.

Wang and Zhang [6] proposed 3-D shape identity matching across domains using a shared kernel transform learning method with the Laplacian-Beltrami operator. The method addresses the difficulty of describing 3-D shape features con-sistently across different domains and is relevant to skull-face identity matching.

Prasad, Sharma, and Singh [7] introduced Cranio-ID, which uses automatic landmark annotation followed by graph-based representation. YOLO-pose models are used for landmark localization, after which cross-modal correspondence is es-tablished through graph representations, cross-attention, and optimal transport.

Prasad and Singh [8] further proposed SPOT-Face, which constructs superpixel-based graphs and uses graph neural networks together with attention-guided optimal transport.

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The objective is to establish structural correspondence between forensic modalities and improve cross-domain identification.

These studies suggest that structural relationships and learned embeddings can provide a stronger basis for skull-to-face matching than direct pixel-level comparison.

D. Facial Recognition and Deep Metric Learning

Facial recognition can play an important role in DVI when reference photographs or facial databases are available. Thote *et al.* [16] investigated an automated face-sketch creation and recognition system using deep learning. Their work demon-strates how generated or forensic sketches can be matched against a database to assist identification.

Sevinc *et al.* [17] investigated Siamese networks, trans-fer learning, and custom deep learning models for forensic identification from human skulls. The study demonstrates the applicability of deep learning architectures for extracting forensic features and performing identification.

Piotrowski *et al.* [4] addressed the broader DVI workflow by developing an ID Victim system consisting of a mobile application, web application, and data server. Their work is particularly relevant to a complete DVI system because it considers not only recognition but also the operational process of victim verification.

Together, these studies indicate that a practical DVI system should integrate image analysis with a structured identification workflow rather than treating facial recognition as an isolated classification problem.

E. Computer Vision and Practical Forensic Reconstruction

Preuß *et al.* [18] presented a computer-aided facial soft-tissue reconstruction workflow based on computer vision and

applied it to forensic cases. Their study illustrates the prac-tical value of combining digital reconstruction with forensic investigation.

Datta *et al.* [19] presented a case involving forensic fa-cial reconstruction of an unidentified deceased individual. The case demonstrates how reconstruction can contribute to identification when conventional methods or reference DNA samples are unavailable. Importantly, the study highlights the complementary relationship between forensic reconstruction and other identification methods.

Wilkinson *et al.* [20] investigated AI-powered avatar and facial depiction technologies, including deepfake and avatar-creation systems.

Although the study focuses on archaeolog-ical facial depiction rather than DVI specifically, it illustrates the increasing capabilities of AI-based facial generation and the need to consider the interpretation and limitations of generated facial representations.

I. *Comparative Analysis*

The reviewed studies can be broadly grouped into five cate-gories: conventional/computer-aided reconstruction, generative reconstruction, cross-domain matching, facial recognition, and soft-tissue/anatomical modelling.

The comparison shows that no single method completely solves the DVI problem. Generative approaches are useful for producing facial approximations, whereas metric-learning and cross-domain approaches are more appropriate for retrieving or verifying identities from a database. Anatomical and soft-tissue studies provide the biological constraints required to make facial reconstruction more meaningful.

II. Research Gaps

Despite significant progress, several research gaps remain.

A. Limited Paired Datasets

Many deep-learning approaches require paired skull and face images. However, such forensic datasets are difficult to collect because of privacy, ethical, and practical constraints. This limitation restricts the generalization of models to real-world disaster cases.

B. Cross-Domain Variation

Skull X-rays, photographs, sketches, and reconstructed faces belong to different visual domains. Although Siamese net-works, graph-based methods, and optimal transport reduce this domain gap, reliable matching remains challenging.

C. Anatomical Variability

Facial soft-tissue thickness varies according to population, age, sex, body characteristics, and measurement conditions. The studies by Hona and Stephan [10], Koza´kova´ *et al.* [11], and Cos¸kun [12] demonstrate why standardized and population-appropriate measurements are important.

D. Reconstruction Uncertainty

A generated face is an approximation and should not be interpreted as an exact representation of the deceased individual.

Generative models may produce visually realistic results while introducing features that are not directly supported by the skull.

E. Need for Forensic Validation

Many machine-learning approaches are evaluated on re-search datasets rather than large-scale real disaster cases. More extensive validation involving forensic experts and realistic DVI scenarios is necessary.

F. Integration of Multiple Evidence Sources

Most reviewed studies focus on one particular modality. A practical DVI system should ideally combine facial images, skull information, landmarks, soft-tissue measurements, demo-graphic information, and available reference databases.

III. Discussion

The literature indicates a clear transition from manually performed forensic facial reconstruction toward automated computer-vision and artificial-intelligence-assisted methods. Early computer-aided approaches focused primarily on reduc-ing reconstruction time, whereas recent research increasingly focuses on learning relationships between skull and facial domains.

Generative models such as CR-GAN and other GAN-based methods can produce visually plausible facial approximations [2], [15]. However, plausibility does not necessarily imply identity accuracy. For DVI, the ability to associate a forensic image with the correct individual is more important than simply generating a realistic face.

Cross-domain recognition methods therefore provide an important complementary direction. Siamese networks [5], graph-based landmark matching [7], and attention-guided op-timal transport [8] attempt to learn structural relationships between different modalities. Such approaches may be partic-ularly useful when a database of potential victims is available. An effective DVI system could consequently use a multi-stage pipeline. First, forensic images could be preprocessed and relevant facial or cranial landmarks detected automatically. Second, deep-learning models could extract features from the available images. Third, cross-domain matching could retrieve candidate identities from a reference database. Finally, facial reconstruction could be used as an additional investigative aid when direct facial evidence is unavailable.

Such a system should not replace established forensic iden-tification procedures. Instead, it should function as a decision-support tool that assists investigators in narrowing candidate identities and prioritizing further forensic examination.

IV. Conclusion

This literature survey reviewed twenty studies relevant to the development of a Disaster Victim Identification System using facial recognition and forensic image analysis. The reviewed research demonstrates significant progress in deep-learning-based facial reconstruction, skull-to-face matching, facial recognition, soft-tissue modelling, automatic landmark detection, and DVI workflow support.

Generative AI and GAN-based approaches demonstrate po-tential for automated facial approximation, while Siamese net-works, graph neural networks, and optimal transport provide promising solutions for cross-domain skull-to-face matching.

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TABLE I
COMPARISON OF REVIEWED METHODS

Ref.	Main Method	Input	Primary Output	Main Contribution
[1]	Computer-aided reconstruction	Skull	Facial approximation	Review of forensic reconstruction
[2]	CR-GAN	Skull image	Facial image	GAN-based reconstruction
[3]	CNN-based reconstruction	Skull image	Facial features	Deep-learning reconstruction
[4]	Deep metric learning	Victim images	Identity verification	DVI system workflow
[5]	Siamese network	Skull + face	Identity ranking	Cross-domain representation
[6]	Kernel transform + LBO	3-D shapes	Identity matching	Cross-domain shape matching
[7]	YOLO-pose + graph matching	X-rays/images	Identity correspondence	Automatic landmarks
[8]	GNN + optimal transport	Forensic images	Matching	Structural cross-domain matching
[9]	Forensic standards	Anatomical data	Standards	Reliability/reproducibility
[10]	FSTT review	Soft-tissue data	FSTT standards	Large-scale FSTT review
[11]	Ultrasound	Facial tissue	FSTT measurements	Head-position effects
[12]	2-D/3-D comparison	CT data	FSTD measurements	Measurement compatibility
[13]	Deep learning + anatomy	Skull	3-D face	Anatomy-guided reconstruction
[14]	Feature mapping	Skull	Facial approximation	Automated mapping
[15]	Generative AI	Skull X-ray	Facial image	GAN-based cross-domain generation
[16]	Deep learning	Face sketch	Recognition	Automated sketch recognition
[17]	Siamese/transfer learning	Skull images	Identification	Deep forensic identification
[18]	Computer vision	Skull/remains	Reconstruction	Practical digital workflow
[19]	Forensic reconstruction	Skull	Facial approximation	Case-based validation
[20]	AI avatar generation	Facial information	Facial depiction	Emerging AI-based depiction

At the same time, anatomical standards and facial soft-tissue measurements remain essential for ensuring that automated reconstruction is grounded in forensic evidence.

The major challenges identified include limited paired datasets, cross-domain variation, anatomical variability, uncer-tainty in generated faces, and insufficient real-world foren-sic validation. Future DVI systems should therefore com-bine deep-learning recognition with anatomical constraints, automatic landmark detection, forensic image analysis, and candidate-based identity retrieval. Such an integrated approach can improve the efficiency of victim identification while maintaining the role of forensic experts in final identification decisions.

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