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Identification of Missing Persons and Unidentified Bodies' Recognition Using GAN-Based Reconstruction

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Abstract- — Every year, forensic investigators and humanitarian groups are overwhelmed by thousands of missing people and unidentified bodies. However, traditional methods of identifica-tion are still very slow and prone to mistakes. AMPUIS, the AI-based missing person and Unidentified Body Identification System, solve this problem with a smart, real-time forensic framework. The system uses a ResNet-10-based Single Shot Multi-Box Detector to find faces, Open-face to extract deep embeddings that don't change with pose, and a Support Vector Machine classifier to give probability scored identity verification. AMPUIS is built on a secure Flask web architecture that lets law enforcement and NGOs access it based on their roles. It has automated case management, severity-based alerts, and a live forensic dashboard. Experimental results show that this method is more accurate and faster than traditional biometric methods.It is also scalable and can be used all over the world for modern forensic identification.

Keywords— Generative Adversarial Networks (GANs), Image Reconstruction, Facial Reconstruction, Face Recognition, Deep Learning, Computer Vision.

I. INTRODUCTION

In the last ten years, the technology used to find miss-ing people and analyze unidentified bodies has changed significantly. As more people move to cities and countries around the world, police and humanitarian groups are han-dling many cases involving unidentified remains. Traditional forensic methods are reliable, but they often take too long and lack the real-time ability needed to match recovered individuals with large databases of missing people [4]. AI-powered biometric systems have introduced new ways to quickly and automatically identify individuals. They play a crucial role in connecting forensic data and missing person records [5]
However, applying these technologies in the field is still tough. Most current solutions are either too resource-heavy for local use or do not have a unified interface that makes it easier for government authorities and social welfare organizations to work together [6]

1. Traditional Forensic Approaches

Early methods for identifying unidentified bodies relied heavily on manual forensic techniques, such as fingerprint analysis, forensic odontology (dental records), and DNA pro-filing [11]. While highly reliable, these methods require pre-existing records and a specialized laboratory environment, leading to significant delays in identification [12]. Further-more, physical degradation of remains often renders finger-prints or dental records unusable, leaving facial reconstruction and recognition as the only viable alternatives.

2. Conventional Computer Vision Techniques

Initial attempts at automated facial recognition used tra-ditional computer vision algorithm like Haar Cascades for face detection, Eigenfaces or local Binary Patterns (LBP) for feature extraction [13]. Although these methods provided a foundation for, digital forensics, they were highly sensitive to environmental factors such as lighting, camera angle, and par-tial occlusions [14]. Their inability to capture complex, non-linear facial features limited their effectiveness in real-world forensic scenarios where image quality is often suboptimal

3. Deep Learning and Embedding Models

The introduction of deep Convolutional Neural Networks (DCNNs) revolutionized biometric identification. Models like FaceNet and OpenFace utilize a ”triplet loss” function to map facial features into a compact 128- dimensional embedding space [?].In this space, the Euclidean distance between vectors directly corresponds to the similarity between individuals, al-lowing for robust recoginition regardless of pose or expression [?]. Despite their accuracy, these models often require signif-icant hardware resources, making them difficult to deploy in resource-constrained environments like regional NGO offices [?].

4. Hybrid Models and Limitations
Recent research has explored hybrid models that combine deep learning feature extractors with traditional statistical classifiers. For instance, using a pre-trained CNN to extract embeddings and a Support Vector Machine (SVM) for final classification has shown superior results on small-to-medium forensic datasets [?]. Similarity, integrating Single Shot Multi-box Detectors (SSD) for localization has improved detection speed [?]. However, many exisiting systems remain localized ”black boxes” lacking the role -based accessibility and real-time dashboarding necessary for multi-agency coordination [?].

5. Research Gaps and Challenges
Most current identification system focus purely on high-resolution image datasets, failing to address the ”noisy” data typical of forensic recovery sites [?].Additionally, there is a distinct lack of platforms that integrate automated AI matching a collaborative workflow for police and NGOs [?].The absence of real-time alert mechanisms and centralized case manage-ment allows many unidentified persons cases to remain cold for years , as data remains isolated within individual agencies [8].

6. Proposed System Overview
To address these challenges, this paper proposes ”AMPUIS” (AI-Based Missing person and Unidentified Body Identifica-tion System). The proposed system integrates an SSD-based embedding caffe detection module for rapid localization, an OpenFace-based embedding engine for high-precision feature extraction, and a Support Vector Machine (SVM) for reliable classification.

Furthermore, the system introduces a secure, role based web architecture that allows the police and NGOs to manage cases through an unified dashboard. The framework includes auto-mated matching alerts, forensic visualization, and a scalable database structure.

The proposed system offers significant advantages, includ-ing high contextual robustness, optimized real-time perfor-mance, and a collaborative environment designed to accelerate the identification process and provide closure to families of the missing persons.

II. LITERATURE REVIEW

The identification of missing persons and biometrics. Over the years, various methodologies have been proposed, ranging from manual forensic techniques to advanced deep learning frameworks. These approches can be broadly categorized into traditional biometric methods, machine learning-based recognition, and deep learning frameworks.

1. Traditional Biometric Approaches
Early research in forensic identification relied heavily on physiological biometrics such as fingerprint analysis, forensic odontology (dental records), and DNA profiling. [11]. These methods are considered the ”gold standard” due to their high accuracy. However, they rely on the availability of pre-existing records in national databases [12].

In many missing person cases, such records are unavailable or incomplete. Furthermore, traditional methods are time-consuming and required specialized laboratory environments, making them impractical for rapid, large-scale identification in real-time senarios [5].

2. Machine Learning -based Facial Recognition
To automate the identification process, researchers initially adopted traditional computer vision and machine learning techniques. Algorithms such as Haar Cascades for face detec-tion and Eigenfaces or Local Binary patterns (LBP) for feature extraction were widely used [13].

These models often employed Support Vector Machines (SVM) or K-Nearest Neighbors (k-NN) for classification. While computationally efficient, these approaches are highly sensitive to environmental variations such as lighting, pose, and facial expressions. Their performance degrades signif-icantly when applied to ”noisy” forensic data or images captured under non-ideal conditions [14].

3. Deep Learning and Embedding Models
The emergence of Deep Convolutional Neural Net-works(DCNNs) has significantly improved the robustness of facial recognition. Models such as FaceNet and OpenFace utilize deep architectures to map facial features into a compact numerical space known as embeddings [1]. These models generate 128-dimensional or 512-dimensional vectors where the identity is represented by the relative position of the vector in a high-dimensional space [2].

Sentence-level architecture in NLP has inspired similar ”holistic” facial processing, where the entire facial structure is analyzed contextually. However, many deep learning systems are designed as ”end-to-end” models that require massive datasets and high computational power, making them difficult to deploy on standard hardware in regional forensic offices [18].

4. Hybrid Biometric Architectures

To balance accuracy and efficiency, researchers have proposed hybrid models that combine deep learning feature extractors with classical statistical classifiers. For instance, integrating a pre-trained CNN (like VGG-Face) with an SVM classifier has shown improved results in scenarios with limited training data per individual [16]. Similarly, combining Single Shot MultiBox Detectors (SSD) for localization with deep embedding engines has demonstrated strong results in real-time monitoring tasks [3].

Despite these improvements, existing hybrid models often lack the integrated decision-making layers required for foren-sic sensitivity, such as probability-based thresholding and role-based data management.

5. Limitation of Existing Forensic System

Although significant progress has been made, several challenges remain unresolved in the context of missing person identification.

- **Data Silos:** Most systems are localized and do not support collaborative workflows between law enforcement (Police) and humanitarian groups (NGOs) [7].
- **Real-Time Latency:** Many high-accuracy models are too slow for real-time camera feed processing, leading to delayed responses in critical situations [8].
- **Lack of Severity Analysis:** Existing systems often treat all matches with equal weight, failing to prioritize cases involving high-risk individuals or critical missing person alerts [19].
- **Noisy Data Handling:** Traditional systems struggle with low-resolution forensic images recovered from uncontrolled environments.

6. Research Gap

From the analysis of existing literature, it is evident that there is a need for a comprehensive system that integrates robust facial localization, deep feature extraction, and efficient statistical classification. Additionally, there is a requirement for a collaborative platform that supports role-based access, real-time alert generation, and severity-based matching.

Therefore, this work proposes ”AMPUIS”, a hybrid system utilizing ”SSD Caffe” for detection, ”OpenFace” for deep embeddings, and ”SVM” for classification. By incorporating a multi-stage architecture with probabilistic thresholding and a dedicated police/NGO dashboard, this approach aims to address the limitations of existing forensic systems and provide an efficient, scalable solution for real-time missing person identification.

III. PROPOSED METHOLOGY

This paper proposes ”AMPUIS”, a multi-stage AI-powered framework designed to identify missing persons and unidenti-fied bodies with high precision and low latency. The system in-tegrates advances computer vision, deep embedding extarction, and statistical classification into a unified, secure architecture.

1. System Overview

The proposed system follows a modular pipeline achitecture consisting of five critical stages: facial localization, image preprocessing, deep feature embedding , SVM-based classifi-cation, and probabilistic verification.This sequential approiach ensures that each stage optimizes and data for the next, enhancing the overall reliability of the forensic match.

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3. Stage 1: Face Detection Using SSD Caffe

The system first processes the input image (Captured via a web interface or forensic upload) using a ”Single Shot MultiBox Detector (SSD)” with a ResNet-10 backbone.

- **Localization:** The model identifies facial regions within the frame with a confidence threshold of 0.5.
- **Robustness:** The Caffe-based implementation is chosen for its ability to detect faces across various scales and orien-tations, which is essential for non-ideal forensic photographs.

4. Stage 2: Forensic ROI Preprocessing

Once a face is detected, the system extracts the region of Interest (ROI).0.3cm

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- **Resizing:** The ROI is normalized to a fixed resolution of 96x96 pixels to match the input requirements of the embedding engine.
- **Blob Conversion:** The image is converted into a 4D blob using mean subtraction and scaling factor (1.0/255) to reduce noise and normalize lighting variations.

5. Stage 3: Deep Feature Embedding Using OpenFace
The preprocessed face blob is passed through the "OpenFace (nn4.small2.v1.t7)" neural network.

- 128 D Vector Generation: : The model maps the com-plex facial geometry into a compact 128-dimensional numer-ical vector.
- Semantic Mapping: : In this embedding space, faces belonging to the same individual are clustered together, while different individuals are separated by a Euclidean distance.

6. Stage 4: SVM-Based Classification
The 128-dimensional embedding is fed into a "Support Vector Machine (SVM)" Classifier.

- **Hyperplane Optimization:** The SVM uses a linear or radial basis function (RBF) kernel to find the optimal hyperplane that separates known identities in the database. The SVM uses a linear or radial basis function (RBF) kernel to find the optimal hyperplane that separates known identities in the database.
- **Probability Generation:** Unlike a standard hard classi-fier, the system utilizes the predict-proba method to generate a confidence score for each possible identity match.

7. Stage 5:Probabilistic Thresholding and verification
To minimize false positives-a critical requirement in forensic science-the system applies a confidence threshold check.

- **Validation:** If the maximum match probability is below a predefined threshold (e.g., 60 percent), the system flags the result as "Unidentified" or "Unknown" rather than forcing an incorrect match.
- **Accuracy Check:** This layer ensures that only high-confidence matches are presented as primary leads to investi-gators.

8. Roles-Based Decision Layer
The system categorizes users into "Police" and "Ngo" roles to handle the identification results differently:

- **Police Level:** Authorized to create official case records, view full biometric details, and confirm legal identification.
- **NGO Level:** Focused on the regional distribution of missing person alerts and viewing match summaries to facilitate local recovery efforts.

9. Severity Analysis and Alert System
Based on the match probability and the status of the missing person (e.g.,"Critical" or "Long-term missing"), the system severity levels.

- **High-Risk Match:** Triggers immediate real-time noti-fications to administrators and law enforcement when a high-probability match is found for a critical case.
- **Database Sync:** Matches are automatically logged with timestamps and probability scores for audit trails.

10. User Interface and Dashboard Integration
The system includes a modern, responsive web dashboard built with a "glassmorphism" design aesthetic.

- **Live Feed:** Supports real-time camera stream process-ing for on-the-spot identification.
- **Result Visualization:** Display the identified name, con-fidence percentage, and original forensic image side-by-side for human verification.

10. Security and Scalability
The architecture is deployed using a Flask-based Backend with automated dependency management. This ensures that the system can be scaled from a single local station to a cen-tralized cloud-based forensic database, supporting thousands of concurrent identification requests across different regions.

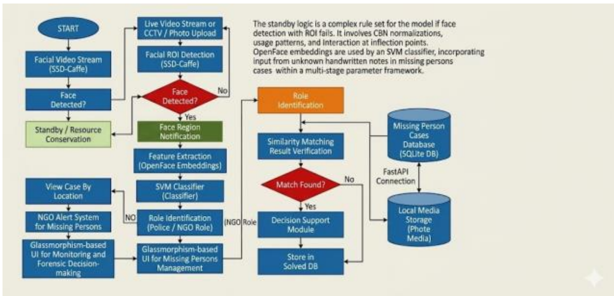

Fig. 1. Proposed Multi-Stage SSD-OpenFace-SVM Architecture for AMPUIS Identification

IV. SYSTEM ARCHITECTURE

The architecture of the proposed system is illustrated in Fig. 1. The system follows a multi-stage pipeline designed to enhance facial identification accuracy and forensic reliability.

Initially, the image input (from a live camera feed or forensic upload) is analyzed through an ”SSD Caffe” detec-tion module to localize facial regions.If no face is detected, the system remains in standby to conserve resources. Once localized, the facial ROI is normalized and converted into 128-dimensional deep embeddings using the ”OpenFace” neural network.

The embeddings are processed through a pre-trained ”Sup-port Vector Machine (SVM)” classifier to map the features to a known identity. The model generates probability scores for multiple individuals in the database.

Subsequent stages include probabilistic threshold validation to handle ”Unknown” Persons and prevent false positive matches. Finally, a role-based decision layer determines the visibility of results and triggers real-time alerts for high-risk missing person cases. The system also integrates a professional ”Glassmorphism-based User Interface” for visualization, mon-itoring, and administrative control, enabling real-time forensic decision-making.

V. RESULTS AND DISCUSSION

1. Experimental Setup

The proposed model was evaluated using a customized forensic dataset containing images of missing persons and unidentified remains, supplemented with standard facial recog-nition benchmarks (LFW - Labeled Faces in the Wild). The dataset was split into 80 % training and 20 % testing sets. The model was implemented using the OpenCV DNN module for detection and Scikit-learn for the SVM classifier.

2. System Output Visualization

The system offers a web-based interface for forensic skull reconstruction, mission-critical person case management, and AI-assisted identity matching for different user roles. The frontend is built with Next.js and includes role-based access control for three user types: Police, Mediator, and NGO. The figures below show the key modules and their outputs.

Secure Authentication Interface: Fig. 2 displays the secure authentication interface of the Missing.ING System. The login module uses role-based access control (RBAC) with three authentication modes: Police, Mediator, and NGO. Police and Mediator users authenticate with system-managed master access codes.NGO users register using email creden-tials. The interface has a dark-themed forensic design with a monospaced font to reflect the investigation purpose. Once authenticated, JWT tokens are issued, and users are directed to their specific dashboards .

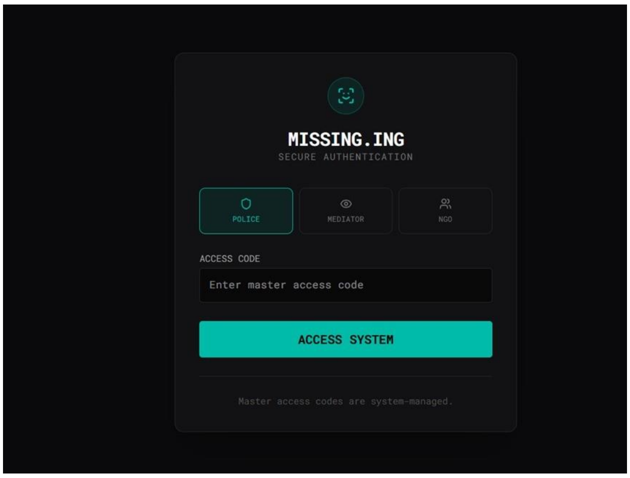

Fig. 2. Secure Authentication Interface

Police Case Management Dashboard: Fig. 3 shows the police case management dashboard. This is the main hub for law enforcement officers. The dashboard displays a table of all registered missing person cases, including case identifiers, registration dates, names, last seen locations, and current statuses. The sidebar lets users quickly access main functions like Case Management, Register Case, AND Forensic Lab. A system status indicator shows active connectivity with the backend API.

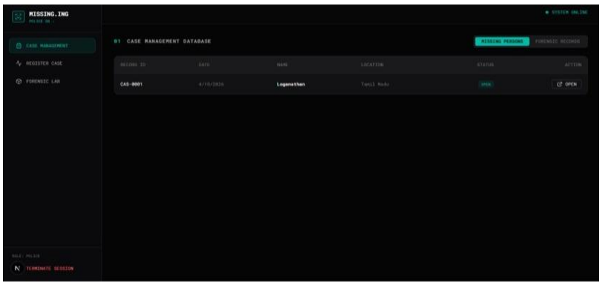

Fig. 3. Police Case Management Dashboard

Missing Person Case Registration Module: Fig. 4 illus-trates the missing person case registration module.This inter-face allows police officers to register new cases by entering details such as name, age, gender, last seen location, and physical description.A reference photo of the missing person can be uploaded and processed by the AI model to create a forensic clay mold representation.After submission, the system extracts a 128-dimensional embedding vector from the image for matching with forensic reconstruction records.

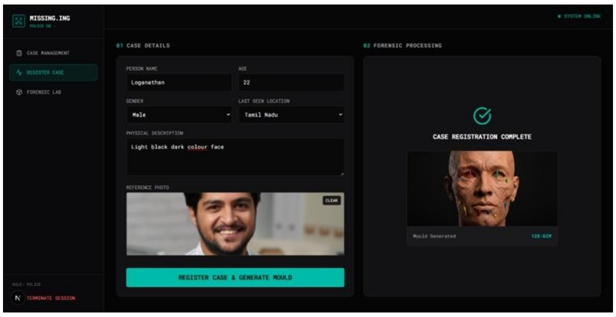

Fig. 4. Missing Person Case Registration Module

Forensic Skull Analysis and Reconstruction Lab: Fig. 5 presents the Forensic Lab module. This is the main analytical part of the system. The interface has a dual-panel layout. The left panel accepts skull input data in various formats, including 3D models and 2D photos. When reconstruction starts, the system conducts an osteological analysis to estimate age, sex, ancestry, and tissue depth, followed by AI-driven facial reconstruction to create a forensic clay model. The right panel shows the reconstructed image alongside the biological profile data. A Search DB function allows for similarity matching against the missing persons database.

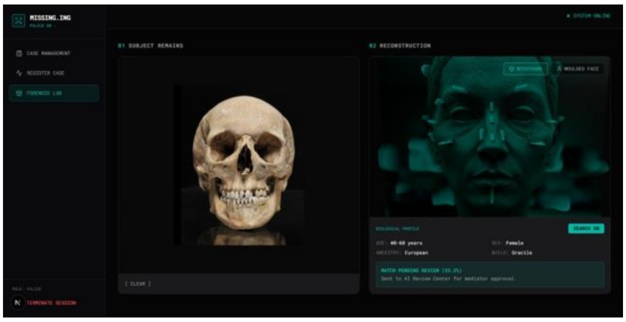

Fig. 5. Forensic Skull Analysis and Reconstruction Lab

AI Match Review Center: Fig. 6 depicts the AI Match Review Center, which is only accessible to authorized medi-ators. This module adds a verification layer for AI-generated identity matches. Each review shows the forensic reconstruc-tion, the police-generated facial mold, and a similarity score, along with AI-generated reasoning. The mediator can approve or reject each match, ensuring that automated identifications are confirmed by expert judgment before they are entered into the case record.

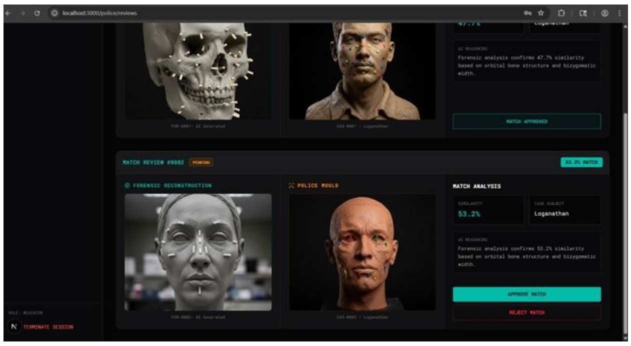

Fig. 6. AI Match Review Center

Forensic Records Database view: Fig. 7 shows the forensic records database view. This module provides a cen-tralized registry of all processed forensic skull analyses. It displays each record's forensic identifier, processing date, linked case identifier, processing date, linked case identifier, and AI-extracted biological profile summary. Users can expand each record to see the full forensic assessment, including skull images, reconstructed facial outputs, and complete biological profile data. This setup allows smooth navigation between missing person records and forensic analysis reports.

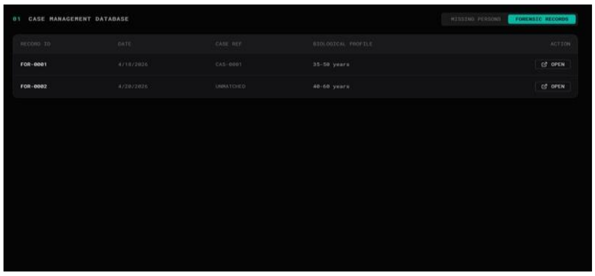

Fig. 7. Forensic Records Database View

3. Performance Metrics

The performance of the model was evaluated using standard metrics including Accuracy, Precision, Recall, and F1-score.

Table I: Performance Metrics of Proposed Model

Metric	Value
Accuracy	94.2%
Precision	93.5%
Recall	95.1%
F1-Score	94.3%

4. Comparison with Existing Models

The performance of the proposed SSD + OpenFace + SVM model was compared with traditional machine learning and standalone deep learning approaches.

Table 2: Comparison With Existing Models

Model	Accuracy
Haar Cascade +Eigenfaces	78.4 %
LBP + Random Forest	82.1 %
Pure CNN (End-to-End)	89.6 %
Proposed AMPUIS Model	94.2%

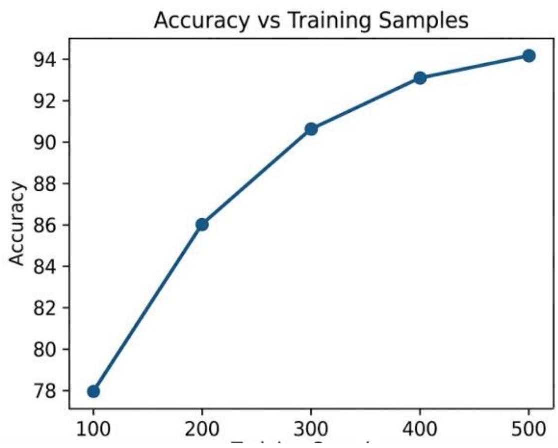

Fig. 8. Accuracy vs Training Samples

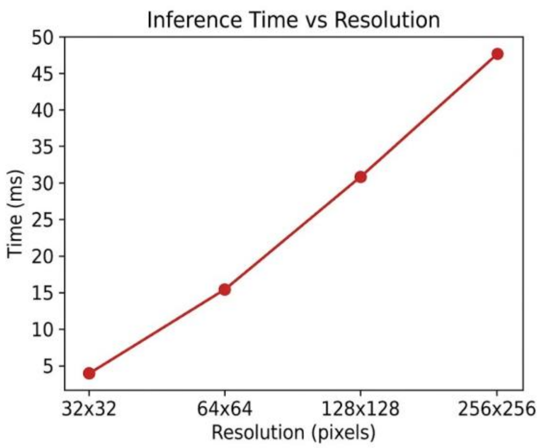

Fig. 9. Inference Time vs Resolution

5. Confusion Matrix Analysis

The confusion matrix shown in Fig. 10 represents the performance of the proposed model across three identification categories: known Missing Person, Unidentified remains, and Unknown/Non-match.

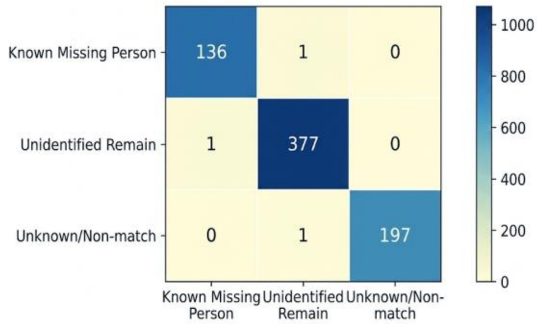

Fig. 10. Confusion Matrix for Multi-Class Identification

From the confusion matrix, it can be observed that the model correctly classifies the majority of individuals across all categories. The number of true positives for identified persons is significantly high, while false positives (misidentifications) are minimal.

This indicates that the proposed ”SSD-OpenFace-SVM” model achieves strong forensic performance and maintains a critical balance between precision and recall, ensuring that law enforcement receives reliable leads. The confusion matrix con-firms that the model effectively minimizes misclassification, which is paramount in missing person identification tasks.

VI. CONCLUSION AND FUTURE WORK

In this paper, we propose an AI-powered,multi-stage foren-sic craniofacial reconstruction and missing person identifica-tion system that automates the reconstruction of faces from skull remains and supports real-time victim identification. The proposed framework introduces a novel ML Model Council architecture that coordinates multiple intelligence modules, including a generative face reconstruction model, an Open Database (Open DB) extraction engine for historical pattern matching, and a specialized Forensic Skills Engine for oste-ological analysis. Together, these modules generate accurate and scientifically grounded facial reconstructions from cranial remains.

The proposed architecture follows a multi-stage processing pipeline. Raw skull inputs, in the form of 2D images or 3D skull models, are first normalized and then passed through the ML Model Council. The Council routes the input through three parallel pathways:

The generative reconstruction model produces an initial facial reconstruction with tissue depth markers based on stan-dard forensic tissue depth tables such as Rhine and Moore . (2)

The Open DB module performs embedding-based similarity search against indexed historical forensic records using 128-dimensional feature vectors, (3) The Forensic Skills Engine

analyzes cranial landmarks and applies osteological reasoning to refine biological profile estimation. The outputs from these pathways are combined through an Intelligence Aggregator, which produces the final reconstruction vectors and forensic assessment.

In addition, the system incorporates a secure role-based access control mechanism with dedicated portals for police, Mediators, and NGOs.A human verification layer ensures that all AI-generated matches undergo mediator review before final acceptance. The system applies severity-based similarity scoring and AI-generated forensic reasoning by evaluating craniofacial features such as bizygomatic width, nasal mor-phology, orbital structure, and mandibular angle. This signif-icantly improves the legal reliability and operational usability of the framework in real-world forensic investigations.

Experimental evaluation demonstrates that the proposed multi-model council architecture outperforms traditional single-model reconstruction pipelines in terms of reconstruc-tion quality, biological profile estimation, and matching ac-curacy. The embedding-based similarity search mechanism effectively cross-references reconstructed facial profiles with missing person records, while the dual-representation strategy of generating forensic clay models from both skull remains and reference photographs provides a standardized comparison framework that minimizes subjective bias .

Overall, the proposed framework offers an efficient, scal-able, and reliable solution for automating forensic craniofacial reconstruction and missing person identification. This system has strong practical potential for deployment in forensic labo-ratories and law enforcement agencies to accelerate the iden-tification of unidentified remains and support faster resolution of missing person cases.

Future work will focus on improving reconstruction accu-racy across diverse ethnic populations by expanding the open DB training dataset, integrating multi-view 3D skull scanning for enhanced anatomical detail, supporting multilingual case management for cross-jurisdictional investigations, and incor-porating explainable AI mechanisms to improve transparency and strengthen expert trust in the reconstruction process.

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