DENTAL PATTERN ENHANCEMENT IN IDENTIFICATION AND VERICATION PROCESS

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***ABSTRACT* — The proposed work introduces a machine learning-based system for dental image classification, developed to enhance identity verification within the Know Your Customer (KYC) process. Unlike conventional approaches that rely on dental X-rays, the system uses camera-captured dental images, offering a more accessible solution for real-world and mobile applications. A custom dataset containing annotated dental photos is organized into training, validation, and testing sets to support structured model development. The YOLOv11n object detection algorithm is employed to detect and localize individual teeth and patterns. These identified features are further processed using convolutional neural networks (CNNs) to build distinct dental profiles for each subject. The classifier pipeline is developed and evaluated through Jupyter notebooks, enabling easy visualization, testing, and performance tuning. The complete system is deployed as a web application using Flask, offering a user-friendly interface for real-time dental classification and identity verification. The proposed work demonstrates the effectiveness of camera-based dental biometrics in secure identity verification, offering potential applications in healthcare, KYC, and related domains.**

I. INTRODUCTION

The Know Your Customer (KYC) process was introduced to combat financial fraud, protect consumer data, and ensure compliance, initially within the banking and finance industries. KYC requires client identity verification, transaction monitoring, and risk assessment, evolving to include advanced technologies like digital documentation and biometric data. In healthcare, KYC now supports secure patient identity management, with dental classification models offering further validation and enhancing data security. Historically, KYC began in the late 20th century as a regulatory response to money laundering and financial crimes, demanding physical customer information collection and manual risk profiling. Its modern applications reflect a shift from basic compliance to comprehensive identity solutions that protect privacy across multiple sectors, including healthcare, where it enhances patient data security and identity management. Verification and identification are core elements of the **Know Your Customer (KYC)** process, ensuring that an individual's identity is both authentic and accurately recorded. Verification involves confirming that provided identity details, such as names and documents, are genuine, often using methods like digital documentation, biometrics, and secure databases. Identification, on the other hand, establishes the distinct attributes of an individual, creating a unique profile used for further interactions and monitoring. In healthcare, this dual approach secures patient information and supports accurate identification, critical for personal health management and regulatory compliance. The integration of verification and identification within KYC not only strengthens data security but also enables seamless, secure service access across multiple sectors. This dual approach is increasingly critical in healthcare, where accurate identification directly impacts patient management, data security, and regulatory compliance, reducing errors and enhancing trust across services.

II. LITERATURE SURVEY

Hong Chen et al. [1] propose using dental radiographs for human identification, which capture details about tooth contours, positions, and dental work (e.g., crowns, fillings, and bridges). The system consists of two main stages: feature extraction and matching. In feature extraction, anisotropic diffusion enhances the images, and a Gaussian model segments the dental work. The matching stage involves three steps: tooth-level matching using shape registration, computing image distances, and subject identification. In tooth-level matching, contours are aligned, and dental work is matched on overlapping areas. The distances between tooth contours and dental work are combined using posterior probabilities. The second step establishes tooth correspondences between postmortem and antemortem radiographs, and a distance metric based on corresponding teeth measures similarity. Finally, the combined distances from the radiographs are used to determine the subject's identity.

Alican Kuran et al. [2] evaluate the effectiveness of YOLO-v5 for automatic detection, segmentation, and numbering of deciduous and permanent teeth in mixed dentition pediatric patients using panoramic radiographs (PRs). The study utilized a dataset of 3854 PRs, labeled for deciduous and permanent teeth, divided into training (80%), validation (10%), and test (10%) subsets. The AI algorithm developed using YOLO-v5 achieved sensitivity, precision, F-1 score, and mean average precision at 0.5 (mAP-0.5) values of 0.99, 0.99, 0.99, and 0.98 for teeth detection, respectively, and 0.98, 0.98, 0.98, and 0.98 for teeth segmentation. YOLO-v5 models show strong potential for accurately detecting and segmenting deciduous and permanent teeth in PRs of pediatric patients with mixed dentition.

Zhenhua Deng et al. [3] address the small-sample problem in dental-based human identification (DHI) by introducing a "classifying while generating" approach. They present the DHI-GAN, a generative adversarial network with an additional classifier to enhance training efficiency. The architecture incorporates identity embedding to retain informative features, while a parallel spatial and channel fusion attention block is designed to focus on relevant details and abstract concepts, improving feature learning. The model utilizes a combination of ArcFace and focal loss to mitigate the small-sample issue. Two parameters control the generated samples during optimization. Validated on a real-world dataset, the DHI-GAN achieves a top-one accuracy of 92.5%, demonstrating its ability to reduce the number of required training samples and integrate with other classification models.

Fei Fan et al. [4] developed an automatic human identification system (DENT-net) using a customized convolutional neural network (CNN) to address the challenge of accurate and fast identification from panoramic dental radiographs (PDRs). The system was trained on 15,369 PDRs from 6300 individuals, with preprocessing steps like affine transformation and histogram equalization. The DENT-net processed 128 × 128 × 7 patches, extracting features from the full PDR and additional details. Feature extraction took approximately 10 milliseconds per image, with a retrieval time of 33.03 milliseconds in a 2000-individual database. The CNN visualization indicated that the teeth, maxilla, and mandible contributed to identification. The DENT-net achieved a Rank-1 accuracy of 85.16% and Rank-5 accuracy of 97.74%, showing high accuracy and speed for human identification. This system could aid human identification in mass disaster and criminal investigations, with final decisions made by specialists.

III. PROPOSED ARCHITECTURE

The proposed work introduces a camera-based dental classification system designed to support secure identity verification in Know Your Customer (KYC) applications. The architecture is built around a modular machine learning pipeline that processes input images through a series of stages including preprocessing, object detection, feature extraction, classification, and verification. (Fig. 1)

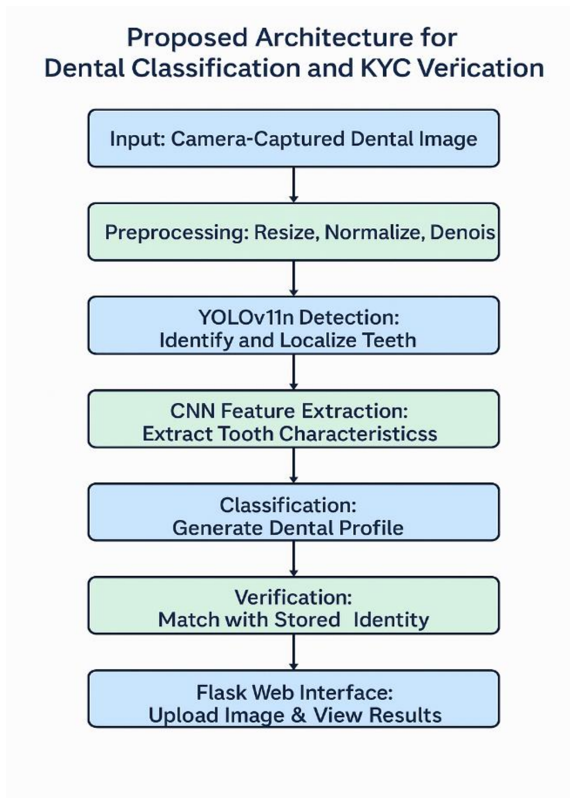

Fig.1 Architecture Diagram

All stages of model development and evaluation are implemented through Jupyter notebooks, enabling interactive testing, visualization of results, and parameter tuning. The final system is deployed using Flask, offering a web-based interface where users can upload dental images and receive classification results in real time. At the initial stage, camera-captured dental images undergo preprocessing to improve their quality and ensure consistency. This step involves resizing, normalizing, and reducing noise in the input images, which helps the model focus on relevant dental features during training and inference. Once preprocessed, the images are passed into a YOLOv11n object detection model. YOLOv11n is selected for its balance of speed and accuracy, allowing the system to detect and localize individual teeth or dental regions efficiently. The detection model is trained on a custom dataset annotated with bounding boxes around teeth, enabling it to generalize well to new images captured in varying lighting and angles. Following object detection, the identified regions of interest are further analyzed using convolutional neural networks (CNNs). These networks extract detailed features from the dental images, such as tooth shape, alignment, gaps, or the presence of dental treatments like fillings or crowns. The CNN model then classifies the input based on these extracted features, helping build a unique dental profile for each individual. This classification output plays a vital role in the identity verification process by linking the observed dental characteristics to stored biometric profiles. To bring the system into a practical and accessible form, the trained models are integrated into a web application built using Flask. This platform allows users to interact with the classification system via a browser, where they can upload dental images and receive instant feedback on detection and classification results. The Flask backend handles image processing, model inference, and result presentation, making the entire process seamless and user-friendly. The proposed architecture, by combining real-time detection with a lightweight deployment model, provides a reliable and scalable solution for identity verification using dental biometrics, without the need for specialized imaging equipment.

IV. ALGORITHM: EXTRACTION PERFORMER

The proposed dental classification system utilizes the YOLOv5n object detection algorithm, which serves as the foundation for the model’s detection and classification capabilities. YOLO (You Only Look Once) models are single-stage object detectors known for balancing speed and accuracy. In this system, YOLOv5n is trained on a custom dataset of camera-based dental images, where each image is annotated with bounding boxes around individual teeth. The model predicts the location and class of each tooth in a sequence

The detection process begins with predicting bounding box coordinates for each tooth. YOLOv5n divides the input image into a grid, and for each cell, it predicts bounding box parameters (b_x, b_y, b_w, b_h), where (b_x, b_y) are the center coordinates, and (b_w, b_h) represent the width and height of the bounding box. These are computed as follows:

$$b_x = \sigma(t_x) + c_x, \quad b_y = \sigma(t_y) + c_y$$
$$b_w = p_w \times e^{(t_w)}, \quad b_h = p_h \times e^{(t_h)}$$

Here, (t_x, t_y, t_w, t_h) are raw outputs from the network, (c_x, c_y) are the coordinates of the grid cell, and (p_w, p_h) are predefined anchor box dimensions. The sigmoid function σ(·) ensures that predicted centers remain within the grid cell boundaries. To evaluate how well a predicted box matches the ground truth, the Intersection over Union (IoU) metric is used:

$$\text{IoU} = (\text{Area of Overlap}) / (\text{Area of Union})$$

A higher IoU indicates a better match between predicted and true bounding boxes. Training is guided by a composite loss function that includes localization loss, confidence loss, and classification loss. The overall loss is defined as:

$$\text{Loss} = \lambda_{\text{coord}} \times \Sigma[(x - \hat{x})^2 + (y - \hat{y})^2 + (w - \hat{w})^2 + (h - \hat{h})^2]$$
$$+ \Sigma_{\text{obj}}(C - \hat{C})^2 + \lambda_{\text{noobj}} \times \Sigma_{\text{noobj}}(C - \hat{C})^2$$
$$+ \Sigma\, \Sigma(p(c) - \hat{p}(c))^2$$

In this equation, (x, y, w, h) are the ground truth bounding box parameters, ($\hat{x}$, $\hat{y}$, $\hat{w}$, $\hat{h}$) are the predicted values, C is the objectiveness score, and p(c) is the predicted class probability. The indicator functions (obj, noobj) specify whether an object is present in the cell. YOLOv5n uses independent sigmoid activations for multi-label classification tasks. The sigmoid function is defined as:

$$\sigma(x) = 1 / (1 + e^{-x})$$

This allows the model to compute the probability of each class independently, which is particularly useful for cases where multiple conditions (e.g., filling and discoloration) may co-occur on a single tooth. By leveraging these mathematical components, the YOLOv5n-based model provides accurate and real-time detection of individual teeth. These outputs are further refined through convolutional neural networks (CNNs) to extract more detailed features for classification. Together, this pipeline forms the backbone of a robust system for identity verification based on dental biometrics.

YOLO Compound Loss Function

The compound loss function used in YOLO-based object detection is defined as:

$$\begin{aligned} Loss &= \lambda_{coord} \times \Sigma_{i=0}^{S^2} \Sigma_{j=0}^{B} \mathbb{1}_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] \\ &+ \lambda_{coord} \times \Sigma_{i=0}^{S^2} \Sigma_{j=0}^{B} \mathbb{1}_{ij}^{obj} [(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2] \\ &+ \Sigma_{i=0}^{S^2} \Sigma_{j=0}^{B} \mathbb{1}_{ij}^{obj} (C_i - \hat{C}_i)^2 \\ &+ \lambda_{noobj} \times \Sigma_{i=0}^{S^2} \Sigma_{j=0}^{B} \mathbb{1}_{ij}^{noobj} (C_i - \hat{C}_i)^2 \\ &+ \Sigma_{i=0}^{S^2} \mathbb{1}_{i}^{obj} \Sigma_{c \in classes} (p_i(c) - \hat{p}_i(c))^2 \end{aligned}$$

Where:

- λ_{coord}: Weight for coordinate loss.
- λ_{noobj}: Weight for no-object confidence loss.
- S: Number of grid cells per image side.
- B: Number of bounding boxes per grid cell.
- $\mathbb{1}_{ij}^{obj}$: 1 if an object is present in cell i, box j; 0 otherwise.
- (x, y, w, h): Ground truth bounding box parameters.
- $(\hat{x}, \hat{y}, \hat{w}, \hat{h})$: Predicted bounding box parameters.
- C, $\hat{C}$: Ground truth and predicted confidence scores.
- p(c), $\hat{p}(c)$: Ground truth and predicted class probabilities.

V. RESULTS AND DISCUSSION

The proposed dental classification system, developed using an object detection model based on the YOLOv5n architecture, was rigorously tested on a dataset composed of dental images captured by conventional cameras (Fig 2).

Fig.2 captured image

The system's effectiveness was evaluated using widely accepted performance metrics including Precision, Recall, F1 Score, and mean Average Precision at an Intersection over Union (IoU) threshold of 0.5. The model achieved exceptional results: a Precision and Recall of 0.99, an F1 Score of 0.99, and a mAP@0.5 of 0.98. These outcomes reflect the model's robust ability to accurately detect and classify individual teeth across varying image conditions.

Several factors contributed to this high performance. The architecture used is optimized for speed and precision, enabling real-time predictions without compromising quality. The training dataset was specifically curated to include diverse examples, enhancing the model's capability to generalize. Data augmentation strategies further helped the model adapt to different lighting, orientation, and image quality conditions (Fig.3 Output).

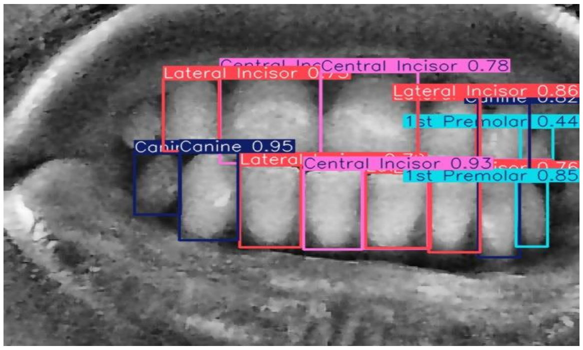

Fig.3 Output

Despite the strong performance, the system encounters challenges when dealing with images of lower quality, obstructed views, or the presence of dental appliances. These factors can reduce the model's accuracy and highlight areas for future improvement. Expanding the dataset, refining image preprocessing, and introducing more advanced post-processing strategies are planned to mitigate these issues.

Overall, the proposed approach shows strong potential for deployment in practical dental diagnostics and biometric identification, combining high accuracy with operational efficiency. Continued development will focus on increasing its resilience in more complex real-world scenarios.

VI. CONCLUSION

The dental classification project harnesses machine learning to enhance identity verification in healthcare by enabling accurate classification of dental images. By utilizing patient data, including dental morphology and medical history, this project aids healthcare providers in efficient patient management. Comprehensive data preprocessing ensures a reliable dataset, while the evaluation of various algorithms identifies the most effective model. With a focus on ethical standards and data diversity, this tool aims to deliver a patient-centered and efficient approach to identity verification in KYC processes.

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