AI-BASED LANDMARK DETECTION FOR CORRELATION OF UPPER PHARYNGEAL AIRWAY AND MANDIBULAR POSITION

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College: *Dayananda Sagar College of Engineering, Bengaluru*
Branch: *Department of Artificial Intelligence & Machine Learning*
Guide(s): *Prof. Ramya K*
Dr. Prachi Kamble
Student(s): *Mr.Abhay Vijay Goudar*
Mr.Gurunathagouda M Biradar
Mr.Mohith Anand
Mr.Pratham Bhat

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Introduction:

Cephalometric analysis plays a crucial role in orthodontics and craniofacial diagnosis, as it helps in evaluating the relationship between skeletal structures, dental alignment, and airway dimensions. Traditionally, this analysis is performed manually by clinicians, requiring precise identification of anatomical landmarks on lateral cephalometric radiographs. However, manual landmark detection is time-consuming, prone to inter-observer variability, and dependent on clinical expertise.

With the advancement of artificial intelligence, particularly deep learning, automated approaches have emerged to improve the accuracy and efficiency of cephalometric analysis. Deep learning models such as convolutional neural networks (CNNs) and U-Net architectures have demonstrated strong performance in medical image analysis tasks, including landmark detection and segmentation.

In addition to skeletal analysis, the evaluation of the upper pharyngeal airway has gained significant importance, as airway dimensions are closely related to respiratory conditions and mandibular positioning. Conventional methods for airway assessment are often limited and lack integration with skeletal analysis.

This project proposes an AI-based system for automatic landmark detection and airway segmentation to analyze the correlation between upper pharyngeal airway dimensions and mandibular position. The system integrates a hybrid deep learning framework, combining heatmap-based U-Net for landmark detection, segmentation-assisted regression models for improved accuracy, and 3D U-Net for volumetric airway analysis.

The proposed approach aims to provide a fully automated pipeline that includes image preprocessing, landmark detection, airway segmentation, cephalometric angle computation, and correlation analysis. Additionally, an interactive interface allows manual refinement of landmarks to ensure clinical reliability.

By combining deep learning with clinical analysis, the system enhances diagnostic accuracy, reduces manual effort, and provides a comprehensive tool for orthodontic evaluation and treatment planning

Objectives:

1. To develop a robust preprocessing pipeline for enhancing and standardizing lateral cephalometric X-ray images and CBCT volumetric data.
2. To design and implement a heatmap-based U-Net model for accurate detection of 11 key cephalometric landmarks using a custom dataset.
3. To develop a segmentation-assisted Convolutional Neural Network (CNN) model for detecting 19 anatomical landmarks with improved precision using publicly available datasets.
4. To integrate a hybrid segmentation-regression approach to enhance landmark localization accuracy by focusing on regions of interest.
5. To implement a 3D U-Net model for precise segmentation of the upper pharyngeal airway from CBCT volumetric data.
6. To compute important cephalometric angles such as SNA, SNB, ANB, SN-GoGn, and Yen angle for skeletal analysis.
7. To measure airway dimensions, including width and volume, from segmented airway regions.
8. To analyze the correlation between mandibular position and airway dimensions using computed parameters.
9. To develop an interactive user interface for visualization and manual adjustment of detected landmarks.
10. To design a backend system for efficient processing, data handling, and integration of deep learning models.
11. To generate automated clinical reports that assist in diagnosis and treatment planning.

Methodology:

The proposed system is designed as an integrated deep learning pipeline for automated cephalometric analysis and airway assessment. The methodology consists of multiple sequential stages, including data acquisition, preprocessing, landmark detection, airway segmentation, and clinical analysis.

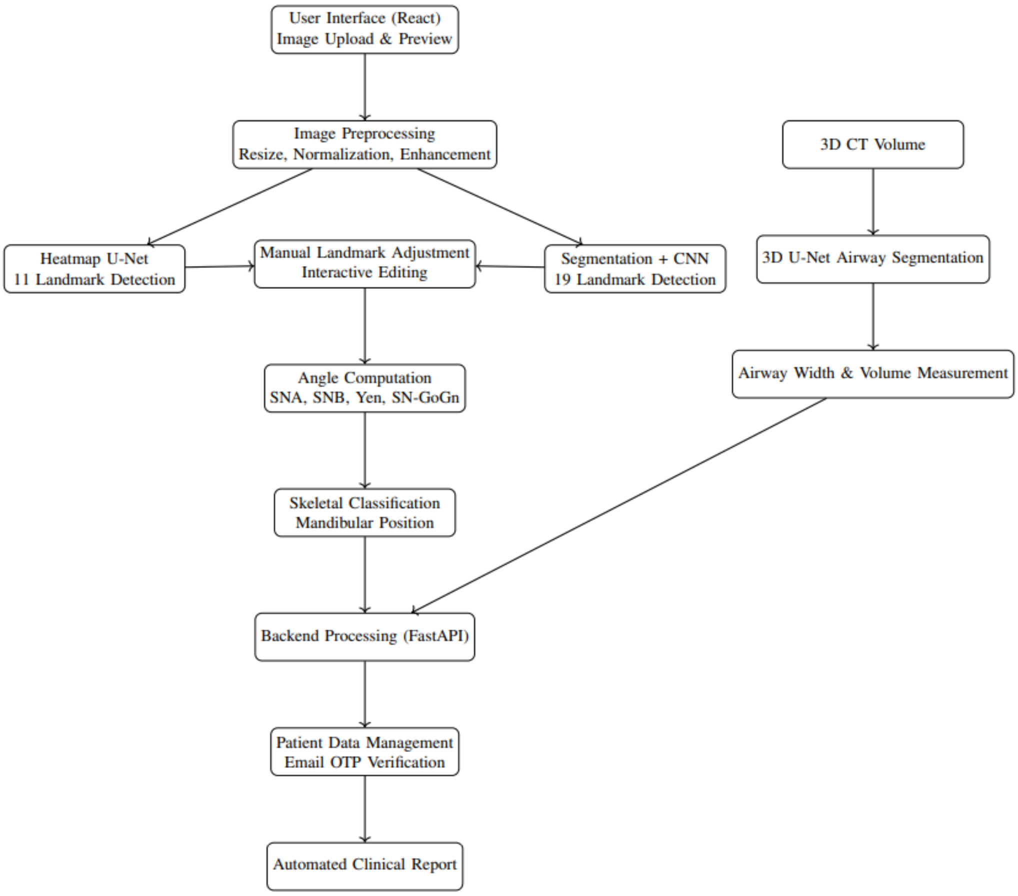

Figure 1:Overall architecture of the proposed framework consisting of three pipelines: (1) heatmap-based U-Net for detecting 11 cephalometric landmarks, (2) segmentation-guided CNN for detecting 19 landmarks, and (3) 3D U-Net for airway segmentation and airway volume estimation.

1. Data Acquisition

The system utilizes both 2D lateral cephalometric radiographs and 3D CBCT volumetric data to ensure comprehensive anatomical analysis.

For 11-landmark detection, a custom dataset consisting of **378 annotated cephalometric images** is used. These annotations are created manually to ensure high accuracy and reliability.

For 19-landmark detection, a larger dataset is constructed by combining publicly available datasets, including ISBI and other sources. This dataset contains **1700 images**, which are divided into **1100 training samples, 300 validation samples, and 300 testing samples**.

For airway analysis, **130 CBCT volumetric scans** are used. These 3D datasets enable accurate segmentation and volumetric measurement of the upper pharyngeal airway.

2. Data Preprocessing

Before training and inference, all input data undergoes preprocessing to standardize and enhance image quality.

The 2D images are resized to appropriate dimensions depending on the model. For landmark detection, images are resized to **320×320 pixels**, while for segmentation tasks, images are resized to **256×256 pixels**.

Pixel values are normalized to a range of 0 to 1, which helps in stabilizing the training process. Image enhancement techniques such as contrast stretching and histogram equalization are applied to improve visibility of anatomical structures.

Noise reduction techniques are also applied to remove unwanted artifacts. Additionally, data augmentation techniques such as rotation, flipping, scaling, and slight translations are used to improve model generalization and reduce overfitting.

3. Hybrid Landmark Detection Framework

To achieve high precision in landmark localization, a hybrid two-stage model is implemented, consisting of segmentation and regression stages.

3.1 Segmentation Stage

In the first stage, a **Convolutional Neural Network (CNN)** is used to generate high-resolution probability masks for anatomical regions of interest. These masks highlight areas where landmarks are most likely to be present.

This stage reduces the search space for landmark detection and improves robustness by focusing on relevant anatomical structures instead of the entire image.

3.2 Regression Stage

In the second stage, the generated masks are used as an attention mechanism for a regression network. The regression model predicts the exact coordinates of landmarks by focusing only on the highlighted regions.

This guided learning approach significantly improves localization accuracy and reduces prediction errors compared to direct coordinate regression.

4. Landmark Detection using Heatmap U-Net

For detecting 11 key anatomical landmarks, a **heatmap-based U-Net architecture** is employed. The model is trained on the custom dataset of 378 images.

Instead of predicting coordinates directly, the model outputs a set of heatmaps, where each heatmap corresponds to a specific landmark. The pixel with the highest intensity in each heatmap is considered the predicted location of that landmark.

The encoder-decoder structure of U-Net, combined with skip connections, allows the model to capture both global context and fine-grained spatial details, resulting in accurate landmark detection.

5. Landmark Detection using Segmentation-Assisted CNN

For extended analysis, a **segmentation-assisted CNN model** is used to detect 19 landmarks. This model is trained on the combined public dataset of 1700 images.

The segmentation output is used to guide the CNN, enabling it to focus on relevant anatomical structures. This improves detection performance, especially for landmarks that are difficult to identify due to overlapping structures or low contrast.

6. Manual Landmark Adjustment

To ensure clinical reliability, the system provides a manual adjustment module implemented using a React-based interface.Users can visually inspect predicted landmarks and adjust them by dragging points on the image. This step allows correction of minor prediction errors and ensures accurate results for clinical use.

7. Cephalometric Angle Computation

To calculate the cephalometric angles, the system uses the coordinates of detected landmarks. These landmarks are converted into vectors, and angles are calculated between these vectors.

The angle between two lines is calculated using the dot product formula:

$$\textbf{theta} = \cos^{-1} \frac{(A * B)}{(|A|\ |B|)}$$

Here, A and B are vectors formed using landmark points.

A vector between two points is calculated as: **AB = (x2 - x1, y2 - y1)**

Using this approach, angles such as **SNA, SNB, ANB, SN-GoGn, and Yen** angle are computed.

The ANB angle is calculated as: **ANB = SNA - SNB**

These angles help in analyzing the relationship between the maxilla and mandible.

8. Skeletal Classification

Based on the computed angles, the system classifies skeletal relationships into different categories such as normal, Class II, or Class III.This classification helps in understanding mandibular alignment and supports orthodontic diagnosis.

9. Airway Segmentation using 3D U-Net

For airway analysis, a **3D U-Net model** is used to segment the upper pharyngeal airway from CBCT volumetric data.The model processes 3D volumes and captures spatial relationships across all dimensions, allowing accurate extraction of airway structures, including nasopharynx, oropharynx, and hypopharynx.

10. Airway Measurement

To measure airway width, the system calculates the distance between two points on the airway boundary using the Euclidean distance formula: $d = \sqrt{(x2 - x1)^2 + (y2 - y1)^2}$

Here, (x1, y1) and (x2, y2) represent the coordinates of two airway boundary points.

For 3D airway analysis, the total airway volume is calculated by summing all segmented voxels: $\text{Volume} = \Sigma\ V\_voxel$ This provides an accurate measurement of the airway space.

11. Correlation Analysis

The system analyzes the relationship between airway measurements and skeletal parameters.By comparing airway dimensions with angles such as SNB and ANB, the system identifies correlations between mandibular position and airway space.

12. System Implementation

The system is implemented using a modern web-based architecture.The backend is developed using FastAPI, which handles model inference, preprocessing, and computations. The frontend is built using React, providing an interactive interface for image upload, visualization, and manual adjustments.Patient data is securely managed, with OTP-based verification for sensitive operations such as data deletion.

13. Automated Report Generation

The system generates a comprehensive clinical report that includes:

- Detected landmarks
- Airway segmentation results
- Cephalometric angles
- Airway measurements
- Skeletal classification

This report assists clinicians in diagnosis and treatment planning.

Training Loss Functions

During training, different loss functions are used for different tasks.

For landmark detection using heatmaps, Mean Squared Error (MSE) loss is used:

$$\text{Loss} = (1/N) * \Sigma (y\_true - y\_pred)^2$$

This helps the model learn accurate landmark positions.

For airway segmentation, Dice coefficient is used:

$$\text{Dice} = (2 * |A \cap B|) / (|A| + |B|)$$

This measures how well the predicted segmentation matches the ground truth.

Result and Conclusion:

The proposed system presents a comprehensive and automated solution for cephalometric analysis and airway assessment by integrating advanced deep learning techniques with clinical evaluation methods.The heatmap-based U-Net model achieved a Success Detection Rate (SDR) of **88.5% at a 4 mm threshold** for 11-landmark detection. The hybrid segmentation-regression model further improved performance, achieving an SDR of **92% at 4 mm** and a Mean Radial Error (MRE) of **1.05 mm**, which is comparable to human-level variability.

For airway analysis, the 3D U-Net model achieved a Dice Similarity Coefficient of **0.96**, demonstrating high accuracy in volumetric segmentation.

Statistical analysis revealed a strong positive correlation between the SNB angle and airway dimensions (**$r = 0.72$, $p < 0.001$**) and a significant negative correlation between the ANB angle and airway space (**$r = -0.66$**), confirming the relationship between mandibular position and airway morphology.

Overall, the system successfully combines landmark detection, airway segmentation, and clinical analysis into a unified framework. It provides accurate, reliable, and clinically meaningful results, making it a valuable tool for orthodontic diagnosis and treatment planning. The integration of AI-driven automation with user interaction further enhances its practical applicability in real-world clinical environments.

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Future Scope:

The future scope of this project includes:

1. The system can be extended by training on larger and more diverse datasets collected from multiple clinical centers to improve robustness and generalization.
2. Advanced deep learning architectures such as transformer-based models and attention mechanisms can be incorporated to enhance landmark detection accuracy.
3. The current 2D landmark detection can be expanded to full 3D craniofacial landmark analysis using CBCT data for more precise diagnosis.
4. Real-time processing can be implemented by optimizing models for faster inference, enabling use during live clinical consultations.
5. The system can be integrated with hospital management systems (HMS) and electronic health records (EHR) for seamless clinical workflow.
6. Cloud-based deployment can be developed to allow remote access, centralized data storage, and scalability.

7. The airway analysis module can be extended to detect and classify respiratory disorders such as sleep apnea.
8. Predictive analytics can be introduced to forecast treatment outcomes based on historical patient data.
9. Mobile or lightweight application development can improve accessibility for clinicians in remote or resource-limited areas.
10. Explainable AI (XAI) techniques can be integrated to provide transparency in model predictions, increasing trust among clinicians.
11. Multi-modal data integration (combining X-rays, CBCT, and patient history) can further improve diagnostic accuracy.
12. Automated treatment planning suggestions can be added as an advanced clinical decision support feature.