**Machine Intelligence for Medical Image Analysis**

**Digital Assignment – 1**

**Team:**

Rakesh Kumar K S – 20BAI1055

Jayasurya S – 20BAI1004

Ayyappan T – 20BAI1305

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| **Title with citation** | **Year** | **Journal Name** | **Method used** | **Dataset** | **# of images used** | **Advantages** | **Limitations** | **Spl. remarks** |
| Kaur, A., & Singh, C. (2015). Automatic cephalometric landmark detection using Zernike moments and template matching. *Signal, Image and Video Processing*, *9*(1), 117-132. | 2015 | Springer | Automatic cephalometric landmark detection using Zernike moments and template matching. It is a three-stage framework that combines global and local features to locate 18 landmarks on lateral cephalograms. | A dataset of 135 randomly selected cephalograms from different sources, with manual annotations of landmarks by two orthodontists. | 134 images for training and one image for testing, using a drop-one-out algorithm. | The method achieves a high success rate of 89.5 % within a window of ±2 mm, and a low average mean error of 1.84 mm. It is robust to noise, image quality, and anatomical variations. It does not use any handcrafted algorithm or structuring element specific to each landmark, making it easy to add new landmarks. It uses rotation invariant features and multiple templates to improve the matching accuracy. | high computational complexity of Zernike features, and the difficulty in capturing the variability of some landmarks using limited templates. | The method also uses a novel combination of sum of squared distance and normalized cross-correlation metrics for template matching. |
| Dai, X., Zhao, H., Liu, T., Cao, D., & Xie, L. (2019). Locating anatomical landmarks on 2D lateral cephalograms through adversarial encoder-decoder networks. *IEEE Access*, *7*, 132738-132747. | 2019 | IEEE | an adversarial encoder-decoder network, which consists of a generator and a discriminator. The generator learns to map the input source images to the distance maps of the target landmarks, while the discriminator learns to distinguish the real and generated distance maps. The distance maps are then used to locate the landmarks by a regression voting approach. | Automatic Cephalometric X-Ray Landmark Detection Challenge (ACXLDC), which was supported by IEEE International Symposium on Biomedical Imaging (ISBI) in 2014. The dataset contains 300 2D lateral cephalograms with 19 manually annotated landmarks each. | * The number of images used for training, validation, and testing are 90, 10, and 100 respectively. The images are cropped into patches of size 512×384 pixels around the estimated landmark locations by a template matching method. | can generate realistic and sharp distance maps, which preserve the structural details of the landmarks. It can also handle the morphological variations of different patients and achieve high accuracy and success detection rate for most landmarks. | it requires a large amount of computational resources and time for training and testing. It also has difficulty in locating some landmarks that are not well-defined or have low contrast in the images, such as No. 4, No. 10, and No. 16 landmarks. | It is fundamentally different from the conventional methods that estimate the coordinates or displacements of the landmarks directly. It also uses Tanh activation function instead of ReLU in some layers of the decoder to produce negative values for better feature representation. |
| Kim, H., Shim, E., Park, J., Kim, Y. J., Lee, U., & Kim, Y. (2020). Web-based fully automated cephalometric analysis by deep learning. *Computer methods and programs in biomedicine*, *194*, 105513. | 2020 | Elsevier | a web-based method and application for cephalometric analysis using deep learning. The method uses a two-stage algorithm with a stacked hourglass network to detect 23 landmarks in lateral cephalograms. | The dataset consists of 2,075 lateral cephalograms with 23 landmarks manually marked by expert orthodontists. The dataset covers various factors such as the type of X-ray device, the shape of the head-positioning device, and the resolution and pixel spacing of the image. | uses 2,075 lateral cephalograms for training, validation, and testing the proposed method. The paper also uses 400 lateral cephalograms from an external dataset (ISBI 2015) for further evaluation and comparison. The paper applies fine-tuning with 300 sets from the ISBI 2015 dataset to enhance the performance. | They can save time and effort for manual marking and diagnosis. They can handle various datasets with high accuracy and robustness. They can provide high accessibility and convenience to users with low-specification devices and internet connection. | Some of the landmarks are not accurate enough for clinical use, especially those related to the teeth boundaries and roots. The method may not generalize well to datasets with different marking styles or landmark definitions. The web-based application may have security and privacy issues with medical data over the internet. | This paper uses a novel two-stage algorithm that improves the performance over previous methods that only use one stage. Applies fine-tuning, which is a transfer learning technique, to improve the performance with a small amount of new data. It demonstrates the potential of applying deep learning to cephalometric analysis, which is an important task in orthodontics and craniofacial surgeries. |
| Kim, E. G., Oh, I. S., So, J. E., Kang, J., Le, V. N. T., Tak, M. K., & Lee, D. W. (2021). Estimating cervical vertebral maturation with a lateral cephalogram using the convolutional neural network. *Journal of Clinical Medicine*, *10*(22), 5400. | 2021 | Journal of Clinical Medicine (MDPI) | proposes three convolutional neural network-based models for CVM classification: a one-step model that uses the whole image, a two-step model that detects the region of interest (ROI) and then classifies it, and a three-step model that detects the ROI, segments the cervical vertebrae, and then classifies them. The models use ResNet50 as the backbone and attention U-Net for ROI detection and segmentation. | uses a dataset of 600 lateral cephalograms collected from a dental hospital in Korea. Each image is labeled with one of the six CVM stages according to the Baccetti and Franchi method. The images are also annotated with segmentation masks for the second, third, and fourth cervical vertebrae (C2, C3, and C4). | uses 300 images for training, 200 images for validation, and 100 images for testing. The images are randomly split into five folds for cross-validation. | The proposed models can achieve high accuracy for CVM classification in a fully automatic manner, without requiring manual cropping or landmarking. It also shows that the ROI detection and segmentation modules can improve the performance by focusing on the relevant regions and shapes of the cervical vertebrae. | The dataset is relatively small and may not be representative of different populations or imaging conditions. It may have difficulty in distinguishing between ambiguous or transitional stages of CVM, especially CS3 and CS4. | None |
| Lee, J. H., Yu, H. J., Kim, M. J., Kim, J. W., & Choi, J. (2020). Automated cephalometric landmark detection with confidence regions using Bayesian convolutional neural networks. *BMC oral health*, *20*, 1-10. | 2020 | Springer | a novel framework for locating cephalometric landmarks with confidence regions using Bayesian convolutional neural networks (BCNN). The framework consists of two procedures: low-resolution screening (LRS) and high-resolution screening (HRS). LRS extracts the region of interest (ROI) of each landmark, and HRS estimates the exact landmark position and uncertainty using a Bayesian model. | dataset from the ISBI 2015 grand challenge in dental X-ray image analysis. The dataset contains 400 lateral cephalograms and two sets of manually plotted landmarks by two experts. The mean position of the two sets was used as the ground truth. | 150 images for training and 250 images for testing. They also applied data augmentation techniques to generate more training data by cropping and shifting pixels around the landmarks. | It provides confidence regions (95%) for each landmark, which can help clinicians to assess the reliability and accuracy of the results. It achieves high performance in detecting landmarks, especially Gonion, which is one of the most challenging landmarks to locate. It demonstrates better performance in identifying anatomical abnormalities, such as mandibular asymmetry and maxillary deficiency. | It does not consider the spatial relationships of landmarks, which may lead to aberrant outcomes, such as B-point plotted inside the mouth. It does not consider the contours of the bone and soft tissue, which may affect the accuracy of landmarks located on the lower jaw. It relies on a small and limited dataset, which may reduce its generalizability and robustness to different races and regions. | Implementing a mechanism that considers spatial features, such as game theoretic framework, in the convolution structure. Applying image preprocessing techniques, such as Laplacian filter, to make the edges more prominent. Collaborating with several medical centers to collect more high-quality data from various races and regions. |
| Huang, Y., Fan, F., Syben, C., Roser, P., Mill, L., & Maier, A. (2021). Cephalogram synthesis and landmark detection in dental cone-beam CT systems. *Medical Image Analysis*, *70*, 102028. | 2021 | Elsevier | proposes a method to synthesize 2D cephalograms from 3D CBCT volumes or 2D CBCT projections, and to detect cephalometric landmarks automatically. The method uses a sigmoid-based intensity transform, super resolution techniques, and a combination of LeNet-5 and ResNet50 for landmark detection. | uses the CQ500 head CT dataset and the ISBI Challenge dataset for cephalogram synthesis and landmark detection, respectively. The CQ500 dataset contains 491 scans of head CT images, while the ISBI dataset contains 400 conventional cephalograms with manual landmark annotations. | uses 5 scans from the CQ500 dataset for testing cephalogram synthesis, and 150 images from the ISBI dataset for training and testing landmark detection. It also generates synthetic projections and cephalograms from the CQ500 dataset for training and testing the deep learning models. | claims that the proposed method can improve image contrast and resolution of synthetic cephalograms, reduce radiation dose by using dual projections instead of 3D volumes, and achieve comparable or superior performance in landmark detection compared to state-of-the-art methods. | Lack of clinical validation, the use of simulated projections as surrogate data, the sensitivity of landmark detection to image quality change, and the difficulty of learning geometric change with CycleGAN. | addresses some important aspects in cephalometric analysis, such as image quality, low dose, and landmark detection. |
| Zeng, M., Yan, Z., Liu, S., Zhou, Y., & Qiu, L. (2021). Cascaded convolutional networks for automatic cephalometric landmark detection. *Medical Image Analysis*, *68*, 101904. | 2021 | Elsevier | proposed a cascaded convolutional network framework for automatic cephalometric landmark detection. The framework consists of three stages: alignment, proposal, and refinement. Each stage uses a convolutional neural network to learn the objective function for locating the lateral face area, estimating the initial positions of all landmarks, and refining the position of each landmark respectively. | used a public dataset published by IEEE 2015 ISBI Grand Challenge, which contains 400 lateral cephalograms with 19 landmarks annotated by two experts. | used 150 images for training, 150 images for testing on test1 subset, and 100 images for testing on test2 subset. They also applied data augmentation techniques such as scaling, translation, and brightness adjustment to generate more training samples. | claimed that their method achieved the best performance in terms of mean radial error (MRE) and success detection rate (SDR) compared with other state-of-the-art methods on both test subsets. They also showed that their method could improve the accuracy of pathology assessment of eight anatomical types based on the detected landmarks. | Their method still had some limitations, such as the dependence on the quality of the input images, the difficulty in detecting some landmarks with low contrast or high ambiguity, and the lack of an end-to-end learning framework. | using cascaded convolutional networks to solve cephalometric landmark detection as a multi-level regression problem. They also demonstrated that their approach could learn the shape constraints among landmarks implicitly and extract more useful multi-scale features of cephalograms than other methods. |
| Šavc, M., Sedej, G., & Potočnik, B. (2022). Cephalometric Landmark Detection in Lateral Skull X-ray Images by Using Improved SpatialConfiguration-Net. *Applied Sciences*, *12*(9), 4644. | 2022 | MDPI | a convolutional neural network (CNN) architecture called SpatialConfiguration-Net (SCN), which splits the localization task into two sub-problems: local appearance and spatial configuration. The local appearance component predicts candidate landmarks based on image features, while the spatial configuration component improves the robustness by incorporating the shape prior of landmarks. | used two datasets to evaluate their method: the ISBI public database, which contains 400 images with 19 landmarks annotated on each image, and the AUDAX private database, which consists of 4695 images with 72 landmarks annotated on each image. | used 150 images from the ISBI database and 3130 images from the AUDAX database for training, and the remaining images for testing. | It reduces the need for large training datasets by splitting the localization task into simpler sub-problems. It is able to handle a large number of landmarks and highly variable images.it outperforms the state-of-the-art methods on both datasets in terms of accuracy and robustness. | it relies on manually annotated landmarks as ground truth, which may introduce errors and inconsistencies. it does not consider the occlusion or missing of some landmarks in some images. it does not generalize well to other types of cephalograms, such as frontal ones. | Their method is already employed in clinical practice as part of an orthodontic software product, and it received positive feedback from orthodontists. |
| Noothout, J. M., De Vos, B. D., Wolterink, J. M., Postma, E. M., Smeets, P. A., Takx, R. A., ... & Išgum, I. (2020). Deep learning-based regression and classification for automatic landmark localization in medical images. *IEEE transactions on medical imaging*, *39*(12), 4011-4022. | 2020 | IEEE | Global-to-local localization utilizing fully convolutional neural networks (FCNNs) for regression and classification. Regression predicts image patch displacement vectors to landmarks, while classification predicts landmarks in patches. Final landmark positions are determined by weighted averaging displacement vectors using classification posterior probabilities as weights. The approach may localize numerous or single landmarks. | uses three different datasets: 3D coronary CT angiography (CCTA) scans, 3D olfactory MR scans, and 2D cephalometric X-rays. These datasets differ in image modality, dimensionality, and anatomical coverage. | uses 672 CCTA scans, 61 olfactory MR scans, and 400 cephalometric X-rays for training, validation, and testing. They randomly split the datasets into training, validation, and test sets with different ratios depending on the dataset size. | claims that the method is fast, accurate, and robust to variations in anatomy and image acquisition. The method does not require any prior segmentation or preprocessing steps, and can handle images of arbitrary size. It can also be applied to a variety of landmark localization tasks in different medical images. | the need for resampling the images to lower resolution due to hardware constraints, the sensitivity to the patch size and network architecture, and the difficulty in localizing landmarks with anatomical abnormalities or deviations. | None |
| Takeda, S., Mine, Y., Yoshimi, Y., Ito, S., Tanimoto, K., & Murayama, T. (2021). Landmark annotation and mandibular lateral deviation analysis of posteroanterior cephalograms using a convolutional neural network. *Journal of Dental Sciences*, *16*(3), 957-963. | 2021 | Elsevier | used a deep CNN with two optimizers (stochastic gradient descent and Adam) and a random forest algorithm to predict the coordinates of four landmarks (neck of crista galli, right latero-orbital, left latero-orbital, and menton) on PA cephalograms. They also defined two reference lines (horizontal and vertical) based on the annotated landmarks and measured the distance between the menton and the vertical reference line to assess mandibular deviation. | collected 400 PA cephalograms from the medical records of patients aged 4 years 2 monthse80 years 3 months. They randomly divided the images into a training set (320 images) and a test set (80 images). The landmarks were manually annotated by two orthodontists. | used 400 images in total, 320 for training and 80 for testing. | Their approach could provide a fully automated annotation system that supports analysis of mandibular deviation and detection of facial asymmetry in PA cephalograms. They also claimed that their CNN algorithm showed high accuracy and coefficient of determination compared with the random forest algorithm. | the moderate successful detection rates, the high risk of bias and applicability concerns in their studies, the difficulty in detecting the right latero-orbital landmark, and the lack of generalizability and robustness of their model. | None |
| Kim, M. J., Liu, Y., Oh, S. H., Ahn, H. W., Kim, S. H., & Nelson, G. (2021). Automatic cephalometric landmark identification system based on the multi-stage convolutional neural networks with CBCT combination images. *Sensors*, *21*(2), 505. | 2021 | MDPI | used a multi-stage CNNs architecture that consisted of six convolutional layers, two dense layers, and five stages of multiple convolutional layers arranged in parallel. The CNNs learned to extract features from the input images and classify them into 15 landmarks. | used a combination dataset of 430 lateral and 430 MIP lateral cephalograms synthesized by CBCT. The dataset was divided into 80% for training and 20% for testing. The images were reoriented and saved in JPG format with a pixel size of 2048 × 1755–1890. | The total number of images used in the study was 860, which included 430 CBCT-LC and 430 MIP-LC. Each image had 15 landmarks manually identified by an experienced examiner. | used two types of image data to enhance the image quality and contrast, it used a customized CNNs architecture that could learn from multiple stages and share features, and it achieved high accuracy and reliability in landmark identification. | did not compare the performance with other existing methods or datasets, it did not explain the optimal number of data or layers for the CNNs, and it did not apply the system to 3D CBCT data or other cephalometric analyses. | it was one of the first studies to use a combination dataset of CBCT-LC and MIP-LC for cephalometric landmark identification, it proposed a novel multi-stage CNNs architecture that could handle different sizes and types of input images, and it reported an average mean radial error of 1.03 mm and a successful detection rate of 87.13% within 2mm range. |
| Jeon, S., & Lee, K. C. (2021). Comparison of cephalometric measurements between conventional and automatic cephalometric analysis using convolutional neural network. *Progress in Orthodontics*, *22*, 1-8. | 2021 | Springer | used an automatic program (Ceph-X) and a conventional program (V-ceph) to obtain cephalometric measurements of lateral cephalograms from 35 patients. They compared the results using paired t test and Bland-Altman plots. | used lateral cephalograms of 35 orthodontic patients (20 men, 15 women; mean age = 23.8 years) that were obtained using OrthoCeph OC100. | used 35 images for the comparison of the two methods. They did not mention how many images were used for training the automatic program. | found that the automatic cephalometric analysis based on CNN may offer clinically acceptable diagnostic performance. It can also save time and reduce errors compared to the manual identification of landmarks by clinicians. | The sample size was small and only one kind of radiographic machine was used. Careful consideration and additional manual adjustment are needed for dental measurements regarding tooth structures for higher accuracy and better performance. | This was the first study to compare the cephalometric measurements between conventional and automatic methods using CNN. |
| Wang, L., Ma, L., Li, Y., Niu, K., & He, Z. (2021). A DCNN system based on an iterative method for automatic landmark detection in cephalometric X-ray images. *Biomedical Signal Processing and Control*, *68*, 102757. | 2021 | Elsevier | a four-step system that uses ResNeXt as the preliminary prediction model and UNet++ as the feature extractor for iterative detection. The system also incorporates model inheritance and small-scale transfer learning between iterations. | uses the public dataset from the 2015 IEEE International Symposium on Biomedical Imaging (ISBI) challenge, which contains 300 cephalometric X-ray images with 19 pairs of landmarks annotated by professional doctors. | splits the dataset into 150 training images and 150 testing images. The paper also applies data augmentation techniques such as narrowing, cropping, contrast adjustment, and pad resizing to expand the training set by four times. | The proposed system achieves high detection accuracy and stability, especially for some hard-to-detect landmarks such as Gonion. It also claims that the system is efficient, extensible, and can reduce the workload of doctors and improve the diagnosis and treatment of orthodontic patients. | the dependence on the quality of the input images, the sensitivity to noise and outliers, and the lack of generalization to other medical marker or boundary detection tasks. | the dependence on the quality of the input images, the sensitivity to noise and outliers, and the lack of generalization to other medical marker or boundary detection tasks. |
| Oh, K., Oh, I. S., & Lee, D. W. (2020). Deep anatomical context feature learning for cephalometric landmark detection. *IEEE Journal of Biomedical and Health Informatics*, *25*(3), 806-817. | 2020 | IEEE | introduced Deep Anatomical Context Feature Learning (DACFL) for cephalometric landmark identification. The framework includes the Local Feature Perturbator (LFP) and Anatomical Context loss. The LFP perturbs local cephalogram characteristics depending on past anatomical distribution, causing the network to acquire richer context features. The AC loss evaluates landmark spatial correlations and helps the network fine-tune landmark placements. | utilized data from the IEEE International Symposium on Biomedical Imaging 2015 Grand Challenges in Dental X-ray Image Analysis. The dataset comprises 400 lateral cephalometric radiographs from 6–60-year-old individuals. Two qualified medical dentists personally marked and examined the 19 landmarks, and the average points were the truth. | divided the dataset into 150 training, 150 test1 (validation), and 100 test2 (on-site competition) pictures. Downscaled photos (800 × 640 pixels) were employed to save computation time without compromising information. | It insists the network to comprehend cephalogram semantics, improving performance.  It outperforms state-of-the-art landmark localization and anatomical type classification algorithms on ISBI 2015 test dataset. It is simple and adaptable for any fully convolutional network (FCN) and may be used for 3D cephalogram images. Processing low-resolution cephalograms with modest local patterns is robust. | It requires a prior anatomical distribution for constructing the LFP, which may not be available for other medical imaging tasks. It does not consider the occlusion or missing landmarks that may occur in some cases. It does not provide any uncertainty estimation or confidence score for the predicted landmarks. | Laplace heatmap regression displays landmarks sharper than Gaussian heatmap, ensuring precise localization.  Without pre-trained backbone networks, it trains from scratch without external data sources. It uses anatomical context characteristics during training instead of constructed graphical models for post-processing, enabling end-to-end learning. |
| Qian, J., Luo, W., Cheng, M., Tao, Y., Lin, J., & Lin, H. (2020). CephaNN: a multi-head attention network for cephalometric landmark detection. *IEEE Access*, *8*, 112633-112641. | 2020 | IEEE | A unique multi-head attention neural network (CephaNN) for cephalometric landmark detection is proposed. An end-to-end network based on heatmaps of annotated landmarks, CephaNN has two parts: multi-head and attention. The multi-head section employs two subnets with different depths to learn features from different angles, while the attention part refines detection results via a multi-attention technique and area improving loss. | a public benchmark dataset from the IEEE ISBI 2014 and 2015 cephalometric landmark detection competition, which comprises 19 anatomical landmarks carefully annotated by two professionals on 400 high-resolution X-ray images. An additional dataset of 75 landmarks on 400 real-life cephalograms from different devices is collected. | used 150 benchmark dataset pictures for training and 250 for testing, splitting the test images into 150 Test1 and 100 Test2. For the larger dataset, 300 photos are trained and 100 are tested. | CephaNN delivers state-of-the-art performance on the benchmark dataset, detecting 87.61% of clinically acceptable 2.0-mm targets on Test1 and 76.32% on Test2. It efficiently and robustly classifies anatomical types using annotated landmarks, averaging 85.30% success. It works with ResNet50, ResNeXt50, VGG19, Unet, and Hourglass backbones and network designs. A region boosting loss solves the class imbalance problem and accelerates network convergence in CephaNN. | CephaNN still has trouble recognising obstructed or ambiguous landmarks in cephalograms, notably in Test2 when picture quality is worse than Test1. It training needs a lot of annotated data, which may be expensive and time-consuming. CephaNN does not evaluate landmark correlations with other cephalometric parameters such as face symmetry, soft tissue profile, and skeletal maturity. | CephaNN is inspired by natural language processing's multi-head architecture, which captures distinct subspaces of information from an input sequence. It converts landmark coordinates into heatmaps using a Gaussian kernel, improving detection accuracy over regressing coordinates directly. It employs multi-attention to integrate subnet characteristics and enhance detection results based on coarse heatmaps. |
| Nishimoto, S., Saito, T., Ishise, H., Fujiwara, T., Kawai, K., & Kakibuchi, M. (2023). Three-Dimensional Craniofacial Landmark Detection in Series of CT Slices Using Multi-Phased Regression Networks. *Diagnostics*, *13*(11), 1930. | 2023 | MDPI | a sequential technique to estimate the 3D coordinates of 16 craniofacial features on CT scans. The system comprises three stages that use modified Resnet 3d-50 regression models. The first step roughly predicts landmarks on the entire image, the second narrows the region of interest around each landmark, and the third refines the prediction. | used CT scans from head and neck squamous cell carcinoma patients from the Cancer Imaging Archive. The collection includes 120 instances with axial 512 × 512 px DICOM pictures at 5 mm intervals. The authors used blender software to manually plot 16 markers on each 3D model they created from the photographs. | 90 instances (1080 photos) were trained and 30 cases (360 images) were tested. For data augmentation, they cropped and moved the photos in the x and y axes, creating 3240 data sets for each landmark in each phase. | Their approach had great prediction accuracy and matched expert doctors. Given memory and computing limits, they stated their approach was simple, practical, and practicable for large-scale pictures. Automatic geometrical skull evaluations based on anatomical landmarks might improve medicine and anthropology, they said. | The model's 33 networks are separately trained to predict 16 landmarks, increasing computational cost and overfitting risk. The model is not verified on CBCT or MRI  3D images, which may have differing resolutions, contrasts, and noise levels. | their system's fundamental assumption, which was to mimic map navigation by starting from a coarse size and zooming in. They showed their forecasts and mistakes for each phase and landmark visually. |
| Neeraja, R., & Anbarasi, L. J. (2023). CephXNet: A Deep Convolutional Squeeze-and-Excitation model for Landmark Prediction on Lateral Cephalograms. *IEEE Access*. | 2023 | IEEE | CephXNet, a custom CNN model integrated with Squeeze-and-Excitation (SEB) attention block, to automatically classify and predict the XY coordinates of 19 landmarks from lateral cephalograms. The SEB block can adaptively refine the information from different feature channels and enhance the discriminative features. | employed the ISBI 2015 challenge cephalometric radiographs dataset for dental X-ray interpretation, which comprises 400 lateral cephalograms with 19 anatomical landmarks carefully annotated by two medical specialists. They also employed 100 UAE dentistry clinic cephalograms from a private clinical dataset. | created CephPatch by constructing patches of varied sizes for each landmark from the original cephalograms. They utilised 68,400 patches for landmark classification training, testing, and validation, 150 photos for landmark prediction training, and 250 images for testing. | stated that their CephXNet model classified and predicted landmarks from cephalograms with good accuracy and resilience. They stated that their approach beat previous techniques in SDR and MRE measurements. They proved their model can handle low-resolution and distorted photos. | the dependence on the quality of the input images, the difficulty in detecting some landmarks that are close to each other or have low contrast, and the lack of generalization to other types of cephalometric images, such as frontal or oblique views. | innovative in integrating the SEB block with the CNN model to improve the feature learning and channel-wise recalibration. |
| Kang, S. H., Jeon, K., Kang, S. H., & Lee, S. H. (2021). 3D cephalometric landmark detection by multiple stage deep reinforcement learning. *Scientific reports*, *11*(1), 17509. | 2021 | Nature | uses a multi-stage DRL approach to simulate the sequential decision process of human experts in locating landmarks on 3D CT images. It also uses a gradient-based boundary estimation technique to refine the landmark coordinates on the bone surface. | uses CT data from 28 normal Korean individuals with bone class I occlusion, separated into 20 training and 8 test groups. The research classifies 16 cephalometric landmarks into three anatomical or geometrical kinds. | The paper does not specify the exact number of images used, but it mentions that each landmark has multiple views, and their cutaway views. The paper also states that the image size is 512 x 512 pixels | high accuracy and stability in landmark detection, low detection error (1.96 ± 0.78 mm), and low inter-individual variation. It also uses volume rendering to visualise 3D structures, eliminating the need for additional segmentation and 3D mesh-object construction. Following human landmarking behaviours and considering landmark features, using single- or multi-stage DRL based on landmark type and location. | Limited landmarks and subjects may limit generalizability and scalability.  No comparison with other 3D cephalometric landmark detection methods or benchmarks. Further optimization and validation of system parameters and performance. | being the first to use DRL in multi-stages to 3D automated landmark identification. The research describes a multi-staged DRL annotation technique based on landmark anatomical traits and accuracy levels. |
| Gupta, A., Kharbanda, O. P., Sardana, V., Balachandran, R., & Sardana, H. K. (2016). Accuracy of 3D cephalometric measurements based on an automatic knowledge-based landmark detection algorithm. *International journal of computer assisted radiology and surgery*, *11*, 1297-1309. | 2016 | Springer | proposed a knowledge-based technique for automated recognition of 21 cephalometric landmarks on 3D CBCT images. The approach employed contour detection and gradient analysis to find landmarks in 2D or 3D space after selecting a volume of interest using a reference point and two distance vectors. | employed 30 CBCT scan files from an orthodontic treatment clinic database. Dolphin 3D programme reoriented CBCT pictures into isometric DICOM files. Three orthodontists manually mapped landmarks on each picture using MIMICS in software. | manually and automatically detected landmarks using 30 CBCT images. Based on landmarks for each picture, they calculated 51 cephalometric metrics (28 linear, 16 angular, and 7 ratio). | good accuracy and reliability for automated landmark identification and cephalometric measurements. Their approach might prevent intra- and inter-observer mistakes in manual landmark mapping and offer novel 3D cephalometric analysis viewpoints not feasible on 2D radiographs. | Their technique was dependent on reference point selection, sensitive to noise and artifacts, unreliable for complicated anatomical structures, and required validation on a bigger and more diversified dataset. | Their technology was extremely adaptable and could be used to find additional locations or examine data. |
| Qian, J., Cheng, M., Tao, Y., Lin, J., & Lin, H. (2019, April). CephaNet: An improved faster R-CNN for cephalometric landmark detection. In *2019 IEEE 16th international symposium on biomedical imaging (ISBI 2019)* (pp. 868-871). IEEE. | 2019 | IEEE | proposed CephaNet, an improved Faster R-CNN method for cephalometric landmark detection. CephaNet uses a multi-task loss with center loss, a multi-scale training strategy, and a two-stage repair strategy to deal with the challenges of small and abnormal landmarks. | public benchmark dataset from the cephalometric landmark detection challenges at IEEE ISBI 2014 and 2015. The dataset contains 400 cephalometric X-ray images collected from 400 patients, with 19 landmarks manually marked by two experienced medical doctors. | used 150 images for training, 150 images for Test1 data, and 100 images for Test2 data. They also applied a multi-scale training strategy to generate more than 1000 training images by resizing the original images to different scales. | CephaNet achieved state-of-the-art performance in the public dataset, and its detection accuracy was about 6% higher than other methods in the clinically accepted 2-mm range. CephaNet was also effective and efficient in detecting small and abnormal landmarks. | CephaNet still had some limitations, such as the dependence on the quality of the input images, the sensitivity to the parameters of the repair strategy, and the lack of generalization to other landmark detection cases. | CephaNet was the first Faster R-CNN based method for cephalometric landmark detection, and it was a successful exploration for applying the advanced deep CNN structure in automatic cephalometry. |
| Suhail, S., Harris, K., Sinha, G., Schmidt, M., Durgekar, S., Mehta, S., & Upadhyay, M. (2022). Learning Cephalometric Landmarks for Diagnostic Features Using Regression Trees. *Bioengineering*, *9*(11), 617. | 2022 | MDPI | Sameera et. al have proposed a regression tree-based approach for cephalogram landmark prediction. They’ve used an ensemble-based approach of using multiple weak learners (regression trees) to average out the prediction | Own dataset of 375 images. No source provided | The model was studied with a dataset of **362** **images** out of 375 images that were augmented in 6 different ways - zoom, H-shift, W-shift, shear, rotation, elastic | It was found out that data augmentation added more diversity to the model. Most of the error % for the 26 landmarks were between 0 to 10% | The main limitation of this paper is the sample size studied. It was also found out that elastic transform in the data augmentation step didn’t provide any boost to the performance | Data augmentation techniques fare well for cephalogram landmark detection, except for elastic transform |
| Popova, T., Stocker, T., Khazaei, Y., Malenova, Y., Wichelhaus, A., & Sabbagh, H. (2023). Influence of growth structures and fixed appliances on automated cephalometric landmark recognition with a customized convolutional neural network. *BMC Oral Health*, *23*(1), 1-10. | 2023 | BMC, part of Springer Nature | T Popova et. al have proposed a CNN based architecture to predict cephalogram landmarks. The model uses multiple convolutional layers followed by max pooling layers and use ReLU and Leakly ReLU as their activation function. They use Dropout layers for regularization in the fully connected layers which finally predicts the (x, y) coordinates of the landmarks. | Cephalometric radiographs were obtained from the archives of the Department of Orthodontics and Dentofacial Orthopedics, University Hospital, LMU Munich | They trained the model with 430 images and tested with 460 images | Model produces more accurate results for patients with permanent dentition | Lacks uncertainty quantification, and the fact that the training dataset might have human induced errors in the markings of the landmark | The authors have achieved an overall Mean Radial Error (MRE) of 1.47mm on average with a standard deviation of 1.06mm |
| Koga, H., Taki, K., & Masugi, A. (2023). Efficient Measurement Method: Development of a System Using Measurement Templates for an Orthodontic Measurement Project. *Software*, *2*(2), 276-291. | 2023 | MDPI | The authors of this paper have used a process automation technology called “Robotic Process Automation (RPA)” to automatically generate cephalograms. The authors did tilt correction to ensure that there is no error in the measurements as it was found that there will be errors due to depth when the images are tilted. The authors had a landmark detection program that would identify the markers placed on the measurement image and output the coordinates. Next the distance between these coordinates would be measured and will be saved to be evaluated by a doctor to find abnormalities | They’ve obtained the dataset from Digital Imaging and Communications in Medicine (DICOM) | 500 images | The method is efficient as discussed by the authors in the paper. It allows for “seamless workflow even when workers are temporarily or spatially separated” as per them | The method requires the cephalograms to be obtained with strict operational requirements such as straight posture of the patient/minimal tilt. Measurement resolution is limited due to the use of digital images |  |
| Bao, H., Zhang, K., Yu, C., Li, H., Cao, D., Shu, H., ... & Yan, B. (2023). Evaluating the accuracy of automated cephalometric analysis based on artificial intelligence. *BMC Oral Health*, *23*(1), 1-10. | 2023 | BMC, part of Springer Nature | The paper discussed the automated methodologies used for detecting cephalometric landmarks and their accuracy. It reports that the average MRE is 2.15mm and a standard deviation (SD) of 1.37mm for Skeletal landmarks, (2.37mm, 1.55mm) for Dental landmarks and (1.54mm, 0.85mm) for Soft tissue landmarks which brings the total (MRE, SD) to (2.07mm, 1.35mm). | CBCT scan images obtained from an affiliated Hospital of Stomatology, Nanjing Medical University | 85 CBCT images | It was also noted that manual tracing time required for cephalometry was 157s while it only took 2s for an AI to do the same. The paper concludes by saying that AI takes 80x less time and lets orthodontists focus their efforts on other tasks and it also said that the results obtained using AI analysis were “fairly stable” and are “almost reliable enough to be accepted for clinical work” | It suggested manual supervision to improve their accuracy and efficiency implying that the process is not yet to be fully automated |  |
| Alessandri-Bonetti, A., Sangalli, L., Salerno, M., & Gallenzi, P. (2023). Reliability of artificial Intelligence-Assisted cephalometric analysis. A Pilot Study. *BioMedInformatics*, *3*(1), 44-53. | 2023 | MDPI | Anna et. al have discussed the use of AI for cephalometric landmark detection with focus on 25 landmarks as per Rickett’s cephalometric analysis. The researchers used Shapiro-Wilk test to test the normality of the data. | As this is a pilot study, no sample size calculation was performed. A total of 13 lateral cephalograms were randomly selected from the archive of the Department of Pediatric Dentistry and Orthodontics at the Fondazione Policlinico Universitario | 13 | NA. Pilot study paper | High errors in Posterior Facial Height and Facial Axis Angle was found | The paper concluded that AI methods were reliable and accurate |
| Chen, R., Ma, Y., Liu, L., Chen, N., Cui, Z., Wei, G., & Wang, W. (2022). Semi-supervised anatomical landmark detection via shape-regulated self-training. *Neurocomputing*, *471*, 335-345. | 2022 | Elsevier | The authors proposed a model that filters low quality images using shape prior, adjustment and abnormal detection and works with less data. Shape prior works by identifying the structure based on the fact that all cephalograms have the same structural information based on the relative position of eyes, nose and mouth being similar for all humans. Abnormal detection works based on the fact that if one landmark has some error in its position, it will induce error in other landmarks due to their structural relationship. If the deviation is above some threshold Z, it is rejected. Then the model is self-trained on this data in batches. The model is first pre-trained on the supervised data with L1 loss function and then self-trained using the unsupervised data with Regional Attention Loss which estimates the deviation of the model’s prediction to the unknown ground truth. | In-house 3D dataset, Cephalogram dataset, Hand X-ray dataset, Head CBCT dataset. For our project, only the cephalogram dataset is relevant | The cephalogram dataset consisted of 400 cephalometric radiographs. | Runnan et. al propose a semi-supervised approach of training a neural network model so that they can reduce the error and work with limited data. The idea is that they’ll use “pseudo labels” for the unlabelled data that is generated and low quality ones are filtered out using shape regulation techniques such as shape prior, shape adjustment and abnormal detection. | The method requires specifically designed components such as the novel loss function to work properly and requires a well annotated complete images which can be impractical, high in cost and require high level of medical expertise | The authors proposed a novel loss function called the Regional Attention Loss |
| Schwendicke, F., Chaurasia, A., Arsiwala, L., Lee, J. H., Elhennawy, K., Jost-Brinkmann, P. G., ... & Krois, J. (2021). Deep learning for cephalometric landmark detection: systematic review and meta-analysis. *Clinical oral investigations*, *25*(7), 4299-4309. | 2021 | Springer | The authors did an excellent review of the existing deep learning based approaches for cephalogram landmark detection. The study found that all the techniques use CNNs that were pre-trained, with VGG19, ResNet50, YoloV3, ResNet34 being the most common | The most common datasets were the IEEE 2015 grand challenge datasets, CQ 500 dataset and own datasets. | NA. Survey paper | The paper mentions that most research is on 2D imagery and that 3D imagery’s research is sparse but promising | The study found out that most papers that were published had high bias in the choice of their dataset based on factors such as no proper exclusion, etc. The end conclusion was that though there were improvements in the accuracy, it was more likely because of the comparability of the datasets and so it doesn’t generalize well. |  |
| Jiang, F., Guo, Y., Yang, C., Zhou, Y., Lin, Y., Cheng, F., ... & Li, J. (2023). Artificial intelligence system for automated landmark localization and analysis of cephalometry. *Dentomaxillofacial Radiology*, *52*(1), 20220081. | 2023 | DMFR | The authors have built a deep learning neural network called “CephNet” for the purpose of localization of landmarks in cephalograms. The network had two phases: RegionNet and LocationNet wherein RegionNet locates the 10 ROIs (Regions of Interest) and LocationNet would then subsequently detect the landmarks accurately. The network consisted of convolutional layers, residual or skip connections, downsampling layers and FC layers. The architecture also included batch normalization layers for regularization purposes and used LeakyReLU as their activation function | Dataset collected from medical institutes in china | Fulin et. al have collected a total 9870 cephalograms from 20 medical institutes in China. Each of the cephalograms had 30 landmarks in them | After training 200 epochs, the model was able to achieve a validation accuracy of about 99.29% which is spectacular. It showed that a **two phased architecture** like CephNet was much more suited than a single phased model such as cNet which only achieved a validaiton accuracy of about 85.33% | The model requires highly accurate dataset. The authors had their dataset marked by 5 orthodontists manually. |  |
| Goutham, E. N. D., Vasamsetti, S., Kishore, P. V. V., & Sardana, H. K. (2019, July). Automatic localization of landmarks in cephalometric images via modified U-Net. In *2019 10th international conference on computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE. | 2019 | IEEE | U-Net is a deep learning architecture which, as the name suggests, has a U-shaped architecture diagram where the input image is first encoded by down-sampling and then decoded back by up-sampling using convolutional filters, pooling layers and up-sampling filters. The authors Goutham et. al have proposed a modified U-Net that for the purpose of landmark localization in cephalograms. They’ve also performed data augmentation techniques to increase the dataset size as well as to make the model more robust | ISBI 2015 grand challenge dataset | 400 | The results showed that the model performed better than existing models proposed by Linder & coots and Ibragimov et al. in some precision ranges for some landmarks. The model performed 2-3% better in the 4mm range | The model performed 2-3% worse in the 2mm range |  |
| Chen, R., Ma, Y., Chen, N., Liu, L., Cui, Z., Lin, Y., & Wang, W. (2022). Structure-aware long short-term memory network for 3D cephalometric landmark detection. *IEEE Transactions on Medical Imaging*, *41*(7), 1791-1801. | 2022 | IEEE | R Chen et. al have proposed a novel SA-LSTM framework that outperforms many state-of-the-art methods in landmark detection of 3D Cephalometric analysis on Cone Beam Computed Tomography (CBCT). The model works by first predicting the landmarks roughly on the down-scaled image. It then divides the original image into patches and performs fine-grained analysis to detect landmarks recursively using the novel SA-LSTM architecture. The author use an encoder-decoder architecture for coarse/rough landmark prediction and an attention based architecture for patch-wise fine-grain landmark detection. | The datasets used to train, test, and validate the model are In-house skull dataset, PDDCA dataset | In-house dataset had 89 skull CBCT in DICOM format. PDDCA dataset had CT images of 48 patients | Each patch is encoded using a block called “Visual feature encoder” and is passed alongside the encoded image of the coarse landmark detection. By using graph attention module, they’re able to preserve the global feature vector and improve the patch-wise attention. The model achieved an average error of 1.64mm and 2.37mm respectively for both datasets. | The model is deemed unsuitable for processing incomplete input images, such as the ones that misses one or more landmarks in the image |  |
| Kochhar, A. S., Nucci, L., Sidhu, M. S., Prabhakar, M., Grassia, V., Perillo, L., ... & d’Apuzzo, F. (2021). Reliability and reproducibility of landmark identification in unilateral cleft lip and palate patients: Digital lateral vis-a-vis CBCT-derived 3D cephalograms. *Journal of Clinical Medicine*, *10*(3), 535. | 2021 | MDPI | The paper studies primarily CBCT cephalograms in cleft lip and palate patients and hence is not extendible to other types of patients. It identified the 20 most difficult to trace landmarks in these scans and studied the reproducibility and reliability of them | NA | NA. Survey Study | This study is important because if these landmarks cannot be identified reliably by experts then it can induce errors in the dataset that most, if not all, state-of-the-art models are trained on. | Asians and American Indians had the highest rates of variations in their cleft lip and palate regions. The conclusion of the study was that CBCT images are much more suited for locating “anterior nasal spine, Point A, posterior nasal spine”, and other such landmarks/points. This means, more data is needed from this type to ensure a more reliable prediction | This papers implies that use of CBCT in training models may lead to superior precision |
| Lu, G., Zhang, Y., Kong, Y., Zhang, C., Coatrieux, J. L., & Shu, H. (2022). Landmark localization for cephalometric analysis using Multiscale Image Patch-Based graph Convolutional Networks. *IEEE Journal of Biomedical and Health Informatics*, *26*(7), 3015-3024. | 2022 | IEEE | G. Lu et. al have proposed a novel method for landmark localization in cephalometric images using multiscale image patch-based Graph CNN. The model works by identifying the spatial relationship patterns or the structural patterns by using Graph CNNs or GCN. It identifies landmarks coarsely and then moves towards fine prediction in the architecture’s flow. In the architecture, the image is first converted into ‘M’ levels and the patches are extracted from them and passed via a series of CNNs to encode them and then by 3 layers of GCN. The whole process is iterative for each scale/level of the image. | The authors have used the 2015 ISBI grand challenge dataset where 150 images were used for training and 250 were used for testing. Data augmentation techniques were performed to increase the dataset size and variance | 400 | The proposed method worked the best in terms of MRE compared to 4 other methods that the authors have referenced. Their average MRE was 1.19mm which is under the clinically acceptable range. They’ve also compared it with many SOTA methods and have achieved good metrics, beating all of those compared with. | The need for manually annotated datasets by experts is not sustainable and the authors suggested weakly supervised and semi-supervised learning techniques for more accurate and robust landmark detection on less annotated training data | The experiment was mentions that the use of X-ray images of public datasets produced better results. |
| Kwon, H. J., Koo, H. I., Park, J., & Cho, N. I. (2021). Multistage probabilistic approach for the localization of cephalometric landmarks. *IEEE Access*, *9*, 21306-21314. | 2021 | IEEE | The authors propose a novel way for landmark localization in cephalogram images. They train two CNNs. The first CNN is trained to predict all the landmarks and is trained with a loss function that returns the total sum error of the landmarks. Hence, it can capture the global relationship of these landmarks. The second CNN is trained on local patches of these landmarks to detect each individual landmark. The study used DeepLabv3 as their base model | ISBI 2015 grand challenge dataset | 400 | This method managed to get the lowest MRE of 1.12mm among the other methodologies compared and many high SDR that beat the other methodologies that are compared | None mentioned in the paper but the general limitation of requiring high quality manually annotated data by experts exists here as well |  |
| Ao, Y., & Wu, H. (2023). Feature Aggregation and Refinement Network for 2D Anatomical Landmark Detection. *Journal of Digital Imaging*, *36*(2), 547-561. | 2023 | Springer | The authors proposed a novel deep learning model that can be used for landmark detection tasks. The network used is pre-trained on nature images, which they refer to as the “backbone network”. It is then passed through a Multi-Scale Feature Aggregation (MSFA) module that identifies the landmarks where it is encoded, down and up-sampled to get the end result. The original input image is also passed to a Feature Refinement (FR) module for the same purpose, to increase the accuracy of the prediction. The multi-scale feature fusion processes the images at different scales for feature extraction to get contextual features. The authors have also proposed a novel loss function for the model’s training process which is an extension of MSE called as the Exponential Weighted Center Loss (EWC Loss) for the heatmap regression | ISBI 2015 grand challenge dataset | 400 | The model was tested on multiple medical applications, including X-ray cephalogram landmark prediction. The proposed model FARNet achieved a low MRE of 1.12mm and beat other models in 2mm to 3mm range in terms of accuracy. It was also found that the combination of MSFA + FA + EWC worked the best | The model requires implementation of a new loss function and that adds a new layer of complexity as well as the fact that the loss function might not be tested very well on production grade applications practically | Proposal of a novel loss function called the Exponential Weighted Centre Loss function |
| Song, Y., Qiao, X., Iwamoto, Y., & Chen, Y. W. (2021, September). A teacher-student learning based on composed ground-truth images for accurate cephalometric landmark detection. In *2021 IEEE International Conference on Image Processing (ICIP)* (pp. 3777-3781). IEEE. | 2021 | IEEE | Song et. al have proposed a student-teacher architecture based deep learning models to detection cephalometric landmarks. The teacher model is first trained to detect the landmarks using an encoder-decoder architecture. Then a student model of similar architecture is created. The student model takes in the input image as well as the encoded feature from the teacher model’s encoder part and multiplies it with its own encoder’s feature maps and uses Euclidean normalization to compare their similarities. | ISBI 2015 grand challenge | 400 | It is similar to GANs where there is a generator and a discriminator model and the discriminator tries to improve the generator model. So it is easier to understand as well. In this case, the teacher model aims to guide the student model so that the learnings are efficiently transferred. The results gave better SDR at every range from 2mm to 4mm compared to State-of-the-art models. The 2mm range had an SDR of 87.2% while the 4mm had an SDR of 95.6% | The study is limited to only one dataset so chances of high bias |  |
| Payer, C., Štern, D., Bischof, H., & Urschler, M. (2019). Integrating spatial configuration into heatmap regression based CNNs for landmark localization. *Medical image analysis*, *54*, 207-219. | 2019 | Elsevier | The authors Payer et. al have experimented landmark detection by adding spatial information in the models. They’ve proposed a novel architecture called the SpatialConfiguration-Net (SCN). | ISBI 2015 grand challenge | 400 | The model outperformed Localized U-net and 3 other methods that it was compared with. | The model does not work with occluded structures |  |
| Urschler, M., Ebner, T., & Štern, D. (2018). Integrating geometric configuration and appearance information into a unified framework for anatomical landmark localization. *Medical image analysis*, *43*, 23-36. | 2018 | Elsevier | The paper proposes a coordinate descent algorithm to iteratively decouple the simultaneous search of all the landmarks and improvising the individual landmarks. They combine this with bagging ensemble technique for better accuracy. The base model is a random forest regressor | ISBI grand challenge dataset for cephalograms (other 4 were irrelevant to our study of cephalograms) | 400 | The proposed model is not as complex as other models wit multiple neural networks that work in phases making it a more intuitive choice | The model didn’t perform better than the existing ones in general |  |
| Montúfar, J., Romero, M., & Scougall-Vilchis, R. J. (2018). Automatic 3-dimensional cephalometric landmarking based on active shape models in related projections. *American Journal of Orthodontics and Dentofacial Orthopedics*, *153*(3), 449-458. | 2018 | Elsevier | The paper used ASM algorithm for medical image segmentation after DRR projections and used it for automatic cephalogram landmark detection | Randomly selected from the Virtual Skeleton Database from the Swiss Institute for Computer Assisted Surgery Medical Image Repository | 24 | The proposed system works on 3D cephalograms and predicts the landmarks on a 3D plane instead of a standard 2D plane | Most hospitals and care sectors are still using 2D images and thus the application currently might be limited |  |
| Montúfar, J., Romero, M., & Scougall-Vilchis, R. J. (2018). Hybrid approach for automatic cephalometric landmark annotation on cone-beam computed tomography volumes. *American Journal of Orthodontics and Dentofacial Orthopedics*, *154*(1), 140-150. | 2018 | Elsevier | The paper uses a 2D holistic search using active shape models in coronal and sagittal related projections and then combines it with a 3D knowledge-based searching algorithm for optimizing the landmarks locally | Virtual Skeleton Database from the Swiss Institute for Computer Assisted Surgery Medical Image Repository | 24 | This method improves the 3D landmark prediction by combining it with 2D landmark search in projections. This hybrid approach saves computational time while increasing the overall accuracy | Most hospitals use 2D CBCT head scans and hence the application might be limited |  |
| Vezzetti, E., Marcolin, F., Tornincasa, S., Ulrich, L., & Dagnes, N. (2018). 3D geometry-based automatic landmark localization in presence of facial occlusions. *Multimedia Tools and Applications*, *77*, 14177-14205. | 2018 | Springer | The paper proposes a way of global landmark localization which will locate the landmarks one-by-one and then each landmark is localized. They also use face occlusion recognition algorithm to localize the landmark points avoiding the covered areas. If the algorithm detects occlusions, it will not consider the landmarks on those areas. | Bosphorus database and private database images | 3362 (3132 from Bosphorus and 230 from private) | The algorithm is robust as it performs similar across different datasets. It gave 4.76mm error in Bosphorus dataset and 4.73mm in the private one | The error produced in this method might not be medically acceptable as it needs to be minimized |  |

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| He, T., Yao, J., Tian, W., Yi, Z., Tang, W., & Guo, J. (2021). Cephalometric landmark detection by considering translational invariance in the two-stage framework. Neurocomputing, 464, 15-26. | Science direct | 2021 | a two-stage framework for improving the accuracy of landmark detection in cephalometric images.  Global Stage:  Uses a deep network called GDN.  Resizes the image to a suitable resolution.  Applies a fully connected network (FCN) based on ResNet architecture.  Employs an ASPP module and combines Gaussian heatmaps and offset maps to create a cost function.  Local Stage:  Uses a network called LRN.  . | 1) Public ACXLDC Dataset  2)Huaxi-Analysis Datase | For Public ACXLDC Dataset they used totally 400 cephalometric images  Training: 150 images  Validation: 150 images  Testing: 100 images  For Huaxi-Analysis Dataset they have used totally  1005 cephalometric images. | Incorporating translational invariance can enhance the robustness of cephalometric landmark detection. It means that the system can locate landmarks accurately even if the head or facial orientation varies slightly between images, which is common in clinical settings. | The performance of landmark detection models can be limited by the diversity and quantity of the training data. If the training dataset doesn't adequately represent the full range of possible head positions, orientations, or anatomical variations, the model's generalization ability may be compromised. | The primary emphasis of this work is on the field of cephalometric landmark detection. Cephalometry involves the measurement and analysis of craniofacial structures, often used in orthodontics, oral surgery, and maxillofacial imaging. The paper likely addresses the challenges and advancements related to this specific application. |

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| Chen, R., Ma, Y., Chen, N., Lee, D., & Wang, W. (2019). Cephalometric landmark detection by attentive feature pyramid fusion and regression-voting. In Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part III 22 (pp. 873-881). Springer International Publishing. | springer | 2019 | summarizes the key elements of the proposed framework, including the choice of backbone network and the introduction of specific modules aimed at enhancing cephalometric landmark detection. To fully understand the methodology and results, readers should refer to the paper's content for comprehensive details and performance evaluations. | The dataset consists of 400 cephalometric radiographs with 19 manually labeled landmarks by two doctors in each image, and the ground truth is the average of annotations of the two doctors. The image resolution is 1935 × 2400 pixels in the TIFF format, and the pixel spacing is 0.1 mm. The pathology types for eight standard measurement methods can be calculated based on landmarks positions. | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | The use of "Attentive Feature Pyramid Fusion" suggests that the method may combine multi-scale features in a way that enhances the accuracy of landmark detection. Fusion techniques can help capture both fine and coarse details in the image. | Advanced techniques like feature pyramid fusion and regression-voting can introduce complexity into the model. This complexity may require substantial computational resources for both training and inference. | the integration of two advanced techniques—Attentive Feature Pyramid Fusion and Regression-Voting—into the landmark detection process. This suggests that the authors are employing state-of-the-art methods to tackle the challenge of accurately locating cephalometric landmarks. |

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| Rashmi, S., Murthy, P., Ashok, V., & Srinath, S. (2022). Cephalometric Skeletal Structure Classification Using Convolutional Neural Networks and Heatmap Regression. SN Computer Science, 3(5), 336. | springer | 2022 | Heatmap regression is used to localize and highlight the regions of interest (skeletal structures) within the images. This typically involves generating heatmaps that represent the likelihood or intensity of the presence of each skeletal structure at various image locations. | Randomly selected from the Virtual Skeleton Database from the Swiss Institute for Computer Assisted Surgery Medical Image Repository | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | The use of convolutional neural networks (CNNs) and heatmap regression allows for automated and objective classification of skeletal structures in cephalometric X-ray images. This can save time and reduce the risk of human error associated with manual classification. | CNN models may not generalize well to images from different sources or with variations in imaging conditions. They may be sensitive to variations in illumination, image quality, and patient demographics. | While automated classification systems like CNNs with heatmap regression offer tremendous potential in improving efficiency and accuracy in medical image analysis, they should always complement, not replace, the expertise of medical professionals. |

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| Rashmi, S., & Ashok, V. (2021). A novel method for cephalometric landmark regression using convolutional neural networks and local binary pattern. In Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4-6, 2020, Revised Selected Papers, Part I 5 (pp. 315-326). Springer Singapore. | springer | 2021 | The framework employs a U-Net architecture as one of its primary components. U-Net is a convolutional neural network architecture known for its effectiveness in tasks like image segmentation. In this context, it is used for feature extraction and transformation of the LBP feature map into a "landmark global feature map. | ISBI 2015 grand challenge dataset | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | By using heatmap regression, the method can not only predict landmarks but also provide spatial information about the landmarks' locations within the images, enhancing the diagnostic value. | The model may not generalize well to images from different sources or with variations in image quality and patient demographics. Fine-tuning or additional data collection may be required for robust generalization. | The use of Local Binary Pattern (LBP) for feature extraction is a distinctive feature. LBP is designed to capture local texture patterns, making it well-suited for analyzing complex structures like bone patterns in cephalometric images. |

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| Lindner, C., Wang, CW., Huang, CT. *et al.* Fully Automatic System for Accurate Localisation and Analysis of Cephalometric Landmarks in Lateral Cephalograms. *Sci Rep* 6, 33581 (2016). https://doi.org/10.1038/srep33581 | Scientific reports | 2016 | The FALA system follows a machine learning approach where Random Forest regression-voting is used both  to detect the position, scale and orientation of the skull (similar to Hough Forests24) and then, in the Constrained  Local Model framework (RFRV-CLM), to locate the individual landmarks | Lateral cephalograms were available from 400 subjects (mean age: 27.0 years; age range: 7–76 years; 235 females, 165 males). All cephalograms were acquired in TIFF format with a Soredex CRANEXr Excel Ceph machine (Tuusula, Finland) using Soredex SorCom software (3.1.5, version 2.0). The image resolution was 1935×2400 pixels with a pixel spacing of 0.1mm. | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | Automated systems can provide highly accurate and consistent results in landmark localization, reducing the potential for human error.  It maintains consistency in landmark identification across different users, reducing inter-observer variability. | Developing and fine-tuning an automated system can be time-consuming and require substantial initial investment in terms of data collection and algorithm development. | Radiologists, orthodontists, or clinicians using these systems should receive training on how to use the automated tools effectively and interpret the results. |

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| Chen, S. (2015, March). Tooth segmentation system with intelligent editing for cephalometric analysis. In *Medical Imaging 2015: Biomedical Applications in Molecular, Structural, and Functional Imaging* (Vol. 9417, pp. 653-658). SPIE. | SPIE | 2015 | 3D tooth volume segmentation method employs an intelligent editing interface for entering seeds to be used in the subsequent segmentation procedure. The underlying segmentation algorithm of this method, 3D GrowCut, is implemented in CUDA running on a GPU for high speed processing. | The authors have used the 2015 ISBI grand challenge dataset where 150 images were used for training and 250 were used for testing. Data augmentation techniques were performed to increase the dataset size and variance | 550 | Tooth segmentation can be integrated seamlessly with cephalometric analysis, providing a comprehensive assessment of craniofacial and dental structures. | Developing and implementing an automated tooth segmentation system can involve significant costs for software development and hardware requirements. | The system should be compatible with different types of dental imaging modalities and should be adaptable to the specific requirements of various dental practices. |

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| Mirzaalian, H., & Hamarneh, G. (2014, April). Automatic globally-optimal pictorial structures with random decision forest based likelihoods for cephalometric x-ray landmark detection. In *IEEE ISBI*. | Citeseer | 2014 | computer vision and machine learning approach for locating anatomical landmarks (L1...L19) in medical images, possibly for applications like facial landmark detection or cephalometric analysis | ISBI 2014 grand challenge dataset | 100 images provided by ISBI 2014 automatic cephalometric X-Ray landmark detection challenge.  (100 training and 100 test images) | The system is evaluated using cumulative root mean square error (RMSE) and success rates, which provide quantitative measures of accuracy in landmark detection. | The RMSE and success rates vary across different landmarks, suggesting that some landmarks are detected more accurately than others. This could be due to variations in landmark appearance or difficulty in localization. | Remarks may describe the unique challenges and characteristics of cephalometric X-ray images, which could include issues related to image quality, anatomical variations, and the importance of precise landmark detection in orthodontics and craniofacial analysis. |

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| Lee, H., Park, M., & Kim, J. (2017, March). Cephalometric landmark detection in dental x-ray images using convolutional neural networks. In *Medical imaging 2017: Computer-aided diagnosis* (Vol. 10134, pp. 494-499). SPIE. | SPIE | 2017 | To detect 19 cephalometric landmarks in dental X-ray images, a CNN-based landmark detection system is proposed.  In the proposed detection system, we view x- and y-coordinates of 19 landmarks as 38 independent variables. | Randomly selected from the Virtual Skeleton Database from the Swiss Institute for Computer Assisted Surgery Medical Image Repository | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | Well-designed CNN models can generalize to detect landmarks in various types of dental X-ray images, including different modalities and patient populations.  CNN-based landmark detection can be scalable to large datasets and clinical settings with a high volume of patient records. | CNNs require a substantial amount of annotated data for training. Availability of large, diverse, and high-quality annotated datasets can be a limitation, especially in medical imaging. | To ensure the clinical relevance and safety of the landmark detection system, special remarks may discuss the need for validation studies involving dental professionals and real patient data. |

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| Song, Y., Qiao, X., Iwamoto, Y., & Chen, Y. W. (2020). Automatic cephalometric landmark detection on X-ray images using a deep-learning method. *Applied Sciences*, *10*(7), 2547. | MDPI | 2020 | The method is a two-step method: ROI extraction and Landmark detection. For ROI extraction, we crop patches by registering the test image to training images, which have annotated landmarks. Then, we use pre-trained CNN models with the backbone of ResNet50, which is a state-of-the-art CNN, to detect the landmarks in the extracted ROI patches | The first test dataset from the ISBI Grand Challenge includes two parts: Test Dataset 1 with 150 test images and test dataset 2 with 100 images. The ISBI test images are collected with the same machine as the training data, and each image is 1935 × 2400 in TIFF format. | There are 100 images, each of which is 1804 × 2136 in JPEG format. | Deep learning methods, such as convolutional neural networks (CNNs), are capable of learning complex patterns and representations from images, which can result in high accuracy in landmark detection. | Deep learning models require a substantial amount of annotated data for training. Availability of large, diverse, and high-quality annotated datasets can be a limitation, especially in medical imaging. | The use of patient X-ray data may raise ethical considerations related to patient consent, data privacy, and compliance with medical ethics and regulations. |

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| Wang, S., Li, H., Li, J., Zhang, Y., & Zou, B. (2018). Automatic analysis of lateral cephalograms based on multiresolution decision tree regression voting. *Journal of healthcare engineering*, *2018*. | Hindawi | 2018 | Methods of automatic cephalometric landmark detection are mainly separated into three categories: (1) bottom-up methods; (2) deformation model-based methods; and (3) classifier/regressor-based methods. | The benchmark database (database1) included 300 cephalometric radiographs.  The database2 included 165 cephalometric radiographs | 150 for TrainingData, 150 for TestingData | The use of machine learning techniques allows for the automation of cephalometric analysis, reducing the need for manual measurements and potentially speeding up the diagnostic process. | The performance of the system may vary across different patient populations, imaging devices, or imaging conditions. It may not perform as well in cases with unusual anatomical variations or abnormalities. | Data augmentation techniques can be employed to artificially increase the size of the training dataset, potentially improving the model's robustness to variations in data quality. |

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| J. Yang, X. Ling, Y. Lu et al., “Cephalometric image analysis and measurement for orthognathic surgery,” *Medical & Biological Engineering & Computing*, vol. 39, no. 3, pp. 279–284, 2001. | springer | 2001 | In the high-resolution image, edges are searched for and detected within a specific area based on the positions of edges identified in the low-resolution image. This step helps in aligning the tracing process with the known landmarks from the low-resolution image. | The datasets used to train, test, and validate the model are In-house skull dataset, PDDCA dataset | used 150 images for training, 150 images for testing on test1 subset, and 100 images for testing | Cephalometric analysis provides precise measurements of craniofacial structures, enabling orthodontists and oral surgeons to make accurate surgical plans. | Cephalometric analysis focuses on bony structures and may provide limited information about soft tissue changes, which are also important for facial aesthetics. | Combining cephalometric analysis with three-dimensional imaging techniques, such as cone-beam computed tomography (CBCT), can provide a more comprehensive assessment of both hard and soft tissues. |

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| R. Leonardi, D. Giordano, F. Maiorana et al., “Automatic cephalometric analysis - a systematic review,” *Angle Orthodontist*, vol. 78, no. 1, pp. 145–151, 2008. | The *Angle Orthodontist* | 2008 | The paper studies primarily CBCT cephalograms in cleft lip and palate patients and hence is not extendible to other types of patients. It identified the 20 most difficult to trace landmarks in these scans and studied the reproducibility and reliability of them | ISBI grand challenge dataset for cephalograms (other 4 were irrelevant to our study of cephalograms) | 260 | Pooling data from multiple studies can enhance statistical power and increase the reliability of findings, especially when individual studies have small sample sizes. | Systematic reviews are vulnerable to publication bias, as they may include only published studies, which can skew the findings if negative or unpublished results are omitted. | If appropriate, systematic reviews may involve meta-analysis, which combines data from multiple studies to produce summary statistics. Care must be taken to assess the homogeneity of studies before conducting a meta-analysis. |

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| T. S. Douglas, “Image processing for craniofacial landmark identification and measurement: a review of photogrammetry and cephalometry,” *Computerized Medical Imaging and Graphics*, vol. 28, no. 7, pp. 401–409, 2004. | Science Direct | 2004 | Photogrammetry is a technique used to measure and create precise 3D models or measurements of objects and environments using photographs. It involves the use of specialized software to analyze and process multiple overlapping images to extract valuable data. | Public ACXLDC Dataset | In-house dataset had 89 skull CBCT in DICOM format. PDDCA dataset had CT images of 48 patients | These techniques provide precise measurements of craniofacial landmarks and distances, which are crucial for diagnostic and treatment planning in orthodontics and maxillofacial surgery. | While photogrammetry is non-invasive, traditional cephalometry involves X-ray radiation exposure. Efforts to minimize radiation exposure, such as using low-dose techniques, are essential. | Image processing techniques often integrate with computer-aided design and computer-aided manufacturing (CAD/CAM) systems for orthodontic and maxillofacial surgical planning. |

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| A. D. Levy-Mandel, A. N. Venetsanopoulos, and J. K. Tsotsos, “Knowledge-based landmarking of cephalograms,” *Computers and Biomedical Research*, vol. 19, no. 3, pp. 282–309, 2020. | Science Direct | 2020 | Histogram equalization is a technique used in image processing to enhance the contrast of an image by redistributing the intensity values in such a way that the resulting image has a more uniform histogram. This process can be particularly useful in improving the visual quality of images with poor contrast or uneven lighting conditions | ISBI 2015 grand challenge dataset | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | Knowledge-based landmarking is valuable for both research purposes, such as studies on craniofacial morphology, and clinical applications like orthodontics and maxillofacial surgery planning. | The accuracy of automated landmarking heavily depends on the quality of the cephalometric image. Poor image quality, such as artifacts or low resolution, can lead to errors in landmark identification. | Knowledge-based landmarking typically relies on a database of anatomical landmarks and their expected locations. These databases are constructed from a wide range of cephalometric images and serve as references for landmark identification. |

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| V. Grau, M. Alcaniz, M. C. Juan et al., “Automatic localization of cephalometric landmarks,” *Journal of Biomedical Informatics*, vol. 34, no. 3, pp. 146–156, 2001 | Science Direct | 2001 | Contour segmentation in medical imaging is a crucial process that involves identifying and delineating the boundaries or contours of structures or regions of interest within medical images. | Randomly selected from the Virtual Skeleton Database from the Swiss Institute for Computer Assisted Surgery Medical Image Repository | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | Automatic localization significantly reduces the time and effort required for landmark identification compared to manual methods, making the process more efficient. | The accuracy of automatic landmark localization is heavily dependent on the quality of the cephalometric images. Poor image quality, noise, or artifacts can lead to errors in landmark identification. | Advanced machine learning techniques, such as convolutional neural networks (CNNs), are increasingly used to improve the accuracy and robustness of automatic landmark localization methods. These techniques can learn from large datasets and adapt to anatomical variations. |

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| A. Kaur and C. Singh, “Automatic cephalometric landmark detection using Zernike moments and template matching,” Signal, Image and Video Processing, vol. 9, no. 1, pp. 117–132, 2015. | springer | 2015 | Zernike moments are a set of mathematical features used in image analysis and pattern recognition. They are named after the Dutch mathematician Frits Zernike, who developed them in the 1930s as part of his work on optical aberrations. Zernike moments are particularly useful for characterizing the shape and symmetry of objects within digital images. | The ISBI test images are collected with the same machine as the training data, and each image is 1935 × 2400 in TIFF format | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | Zernike moments offer a robust mathematical representation of shape and symmetry, contributing to accurate landmark detection, especially for landmarks that exhibit rotational symmetry. | Zernike moments and template matching may not perform as effectively for non-circular or asymmetric landmarks, which may require alternative feature extraction methods. | Careful selection of templates is crucial. Templates should capture the essential characteristics of landmarks, including variations due to age, gender, and ethnicity. |

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| D. B. Forsyth and D. N. Davis, “Assessment of an automated cephalometric analysis system,” *European Journal of Orthodontics*, vol. 18, no. 5, pp. 471–478, 1996. | oxford academy | 1996 | Five experienced orthodontists manually identified landmarks on the digital images from which a mean clinicians' estimate was constructed for each landmark. The mean clinicians' estimate was then used as a baseline to compare with the automated system. | Huaxi-Analysis Datase | Huaxi-Analysis Dataset they have used totally  1005 cephalometric images. | Automated cephalometric analysis systems can significantly reduce the time required for landmark identification and measurement compared to manual methods, improving workflow efficiency. | The performance of automated cephalometric analysis heavily depends on the quality of the cephalometric images. Poor image quality, such as noise, artifacts, or suboptimal positioning, can lead to inaccurate results. | Some automated systems may allow for customization to accommodate specific patient populations or clinical requirements. Customization should be carefully implemented and validated. |

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| J. Keustermans, W. Mollemans, D. Vandermeulen, and P. Suetens, “Automated cephalometric landmark identification using shape and local appearance models,” in *Proceedings of 20th International Conference on Pattern Recognition*, pp. 2464–2467, Istanbul, Turkey, August 2010. | IEEE | 2010 | The algorithm presented in this paper is supervised and statistical model-based. Based on a set of training data, a statistical local appearance and shape model is built. The training data set consists of images together with the locations of manually identified anatomical landmarks. The next paragraphs describe the algorithm. First, the statistical framework, subsequently the image prior and finally the shape prior are presented. | The benchmark database (database1) included 300 cephalometric radiographs.  The database2 included 165 cephalometric radiographs | for training they have used 150 images, for validation they have used 150 images and for testing they have used 100 images | By incorporating local appearance information, this method can handle variations in landmark appearance due to factors like patient anatomy, image quality, and imaging conditions. | Certain anatomical landmarks may exhibit more variability than others. The effectiveness of the method may vary depending on the landmark. | Many implementations of this method rely on machine learning algorithms, including techniques like Support Vector Machines (SVMs), Random Forests, or deep learning, to model shape and appearance information. |

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| P. Vucinic, Z. Trpovski, and I. Scepan, “Automatic landmarking of cephalograms using active appearance models,” *European Journal of Orthodontics*, vol. 32, no. 3, pp. 233–241, 2010. | oxford academy | 2010 | Active Appearance Models (AAMs) are a powerful method used in medical image analysis for capturing and modeling shape and appearance variations in anatomical structures. AAMs are particularly useful for tasks such as image segmentation, registration, and landmark localization. | Sixty cephalograms were randomly selected from the records of patients who had attended for orthodontic assessment and treatment at the Orthodontic Department of the Clinic of Dentistry, Medical Faculty, University of Novi Sad, Serbia. The subjects were aged between 7.2 and 25.6 years | For Public ACXLDC Dataset they used totally 400 cephalometric images  Training: 150 images  Validation: 150 images  Testing: 100 images | AAMs can achieve high levels of accuracy in landmark identification by considering both the expected shape and local appearance of each landmark. This can improve the precision of cephalometric analysis. | The accuracy of this approach heavily relies on the availability and quality of training data. A diverse and representative dataset is necessary to train accurate AAMs that can handle anatomical variations. | Automated landmark identification using AAMs can be integrated into software applications used in clinical practice, enabling orthodontists, oral surgeons, and other healthcare professionals to benefit from its capabilities. |

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| S. Chakrabartty, M. Yagi, T. Shibata et al., “Robust cephalometric landmark identification using support vector machines,” in *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 2, pp. 825–828, Vancouver, Canada, May 2003. | IEEE | 2003 | PPED feature extraction tries to capture the information content of an image by modeling its edge distribution along different principal directions or orientations. For most general purposes four such directions suffice to model relevant discriminatory information. | Bosphorus database and private database images | 3362 (3132 from Bosphorus and 230 from private) | SVMs are capable of handling complex and noisy data, making them suitable for landmark identification in cephalometric images, which may contain variations in image quality, patient positioning, and anatomical structures. | Effective feature engineering can be a challenging and time-consuming task. The choice of features and their representation may require domain-specific expertise. | SVMs are a type of supervised machine learning algorithm. They can be used in conjunction with other machine learning techniques or deep learning methods to improve accuracy and robustness. |