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Research Article

Unleashing hidden canines: a novel fast R-CNN based technique for automatic auxiliary canine impaction

S.Deepa[1], A.Umamageswari[2*],L.Sherinbeevi[3] and A.Sangari[4]
Assistant Professor, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, India[1]
Associate Professor, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, India[2]
Assistant Professor, Department of Computer Science and Engineering, R.M.D Engineering College, Kavaraipettai, Tamilnadu, India[3]
Associate Professor, Department of Electrical and Electronics Engineering, Rajalakshmi Engineering College, Thandalam,Tamilnadu, India[4]

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Abstract
Orthodontic treatment, including impacted canines, is a complex process that requires accurate and timely detection. Traditional methods for identifying impacted canines typically rely on manual inspection, which can lead to human errors and time-consuming processes. Canine impaction analysis has numerous applications across various fields such as aesthetics, self-esteem, early intervention, maxillofacial health, and improved quality of life. By leveraging the power of deep learning, this model aims to revolutionize the field of orthodonture and contribute to improved patient outcomes. An approach has been proposed that utilizes image processing methods combined with fast region-based convolutional neural networks (fast R-CNN) to automatically detect impacted canines. This method streamlines the diagnosis process and enhances the accuracy of treatment planning. The method also employs Python for statistical analysis to determine whether treatment for canine impaction is feasible. The proposed method has demonstrated high performance with an accuracy of 98.3%. This collaboration is crucial to ensure the responsible and effective integration of this technology into clinical workflows, ensuring its seamless incorporation with ethical considerations for optimal effectiveness.

Keywords
Fast R-CNN, Maxillary canine impaction, Statistical analysis, Deep leaning, Orthodontic treatment.

1.Introduction
The field of orthodontics has witnessed rapid advancements in diagnostic technologies, enabling early identification and targeted treatment of various dental anomalies. Canine impaction, being one of the most common malocclusions, requires precise and prompt detection to ensure optimal outcomes [1]. The objective of using artificial intelligence (AI) in the context of maxillary canine impactions is to enhance diagnostic accuracy, treatment planning, and overall outcomes in dental and orthodontic procedures. AI can analyze complex datasets, including radiographic images and patient records, to identify patterns and provide valuable insights for clinicians.

By leveraging AI, healthcare professionals can achieve a more precise understanding of maxillary canine impactions, leading to improved decision-making, personalized treatment strategies, and ultimately, better patient care.

Traditional methods of diagnosing impactions are labor-intensive and prone to human error. In this context, it proposes a cutting-edge convolutional neural network (CNN)based technique that promises to revolutionize the way orthodontists identify and manage auxiliary canine impactions [2].

The motivation behind AI-based auxiliary canine impaction diagnosis and management is to enhance the quality of dental care, improve patient outcomes, and leverage the capabilities of AI to provide more precise and efficient solutions in the field of dentistry like

*Author for correspondence

improved diagnosis accuracy, early intervention, reduced diagnostic errors, efficiency and productivity, and research and knowledge advancement [3, 4].Dental malocclusions, or misalignments of teeth, are a common concern in orthodontic practice. One specific type of malocclusion that orthodontists frequently encounter is canine impaction.

Canine impaction refers to the condition where the permanent canines, also known as "eye teeth" or "fangs," fail to erupt into their natural positions in the dental arch during the normal developmental process. The canines are crucial for proper occlusion and a harmonious smile. They play a pivotal role in cutting and tearing food, maintaining facial aesthetics, and supporting neighboring teeth. When canines become impacted, they may remain buried in the jawbone or incorrectly positioned, leading to various oral health issues and cosmetic concerns. While the majority of individuals have their canines erupt normally, certain factors can contribute to the impaction of these critical teeth. One primary cause is a lack of adequate space in the dental arch, which may be attributed to genetic predisposition, early loss of primary teeth, or abnormal growth patterns of the jaw [5]. In some cases, retained primary teeth or abnormal tissue growth can also hinder the eruption of permanent canines. The diagnosis of auxiliary canine impaction typically involves a comprehensive dental examination, including clinical evaluation, dental radiographs (X-rays), and possibly three-dimensional (3D) imaging. Orthodontists care-fully assess the position of the canines and sur-rounding structures to determine the appropriate treatment approach [6]. Timely detection of auxiliary canine impaction is crucial for successful management and treatment planning. Early intervention allows orthodontic professionals to initiate appropriate measures to guide the impacted canines into their proper positions or make space for them through orthodontic appliances or surgical procedures [7].

In recent years, advances in diagnostic technologies, such as computer-based techniques, have shown great promise in aiding orthodontists in the early and accurate identification of canine impactions. These advancements offer the potential for more efficient and precise diagnoses, leading to improved treatment outcomes and enhanced patient care [8].

This study aimed to enhance the accuracy and efficiency of diagnosing auxiliary canine impaction in orthodontics through the application of advanced image processing and deep learning techniques. The primary contribution is the development and validation of a fast region-based convolutional neural network (fast R-CNN) model that automates the detection of impacted canines from dental radiographic images. By integrating this model, the aim is to reduce the reliance on manual inspection, which is often prone to errors and time-consuming. The fast R-CNN model not only improves diagnostic precision but also streamlines the treatment planning process, thereby promising substantial improvements in patient outcomes. The effectiveness of this approach is demonstrated through rigorous testing against a comprehensive dataset, showcasing the model's ability to deliver high accuracy and reliability in identifying impacted canines, thus marking a significant advancement in the field of dental diagnostics and orthodontic care.

This paper is structured as follows: Section 2 elaborates on the literature review. Section 3 describes the algorithms of the proposed method. The dataset used for experimentation and result analysis is detailed in Section 4. Section 5 provides a detailed analysis of the results obtained and compares them with existing techniques. The paper concludes in Section 6, summarizing the research findings and providing directions for future analysis.

2.Literature review

Several previous studies have explored computer-aided methods for detecting impacted canines using image processing techniques. However, the limitations of these methods include lower accuracy lev-els and higher sensitivity to variations in image quality and feature extraction.

Fontenele et al. (2022) [1] validated an AI tool for tooth segmentation on cone-beam computed tomography (CBCT) images, assessing its performance with different dental fillings and tooth types. They com-pared AI segmentation to manual expert segmentation. Limitations could include biases in image se-lection, image quality affecting AI accuracy, and potential limited generalizability to diverse dental conditions or populations. Vila-blanco et al. (2022) introduced explainable age and sex (XAS), an AI method for XAS determination using dental images. It combines predictions from individual teeth for accuracy and emphasizes explainability. The study likely involved testing XAS on datasets with known XAS labels. Potential limitations include variability across populations and generalizability to diverse dental conditions [9]. Limitations could include potential biases in the training data, variations in image quality affecting algorithm performance, and the need for further validation on diverse datasets to assess generalizability [10]. CNN have demonstrated outstanding performance in various image recognition tasks, motivating our choice to explore this deep learning approach for automatic canine impaction detection [11-13]. Pinheiro et al. (2021) [13] developed a deep learning model for numbering permanent and deciduous teeth in panoramic X-rays using instance segmentation. They trained the model on a dataset of X-ray images and likely evaluated its performance with accuracy metrics. Limitations might involve handling variations in image quality and potential errors in automated numbering [14]. Research and studies that discuss the use of AI algorithms in dental imaging, such as panoramic CBCT X-rays, or intraoral radiographs, for identifying impacted canines and other dental abnormalities. Studies that focus on the development and validation of AI algorithms specifically designed for diagnosing and detecting impacted canines [15-17]. This could include deep learning models, CNN, or other AI approaches. Research that explores the integration of AI in treatment planning for impacted canines, including evaluating the feasibility of AI-guided decision-making in selecting the most appropriate treatment options [18]. Bichu et al. (2021) [18] conducted a scoping review on AI and machine learning (ML) applications in orthodontics. They systematically analyzed literature to identify methods, effectiveness, and challenges. The review likely covered various AI/ML techniques used in orthodontic practices. Limitations may include the scope and depth of available literature and the evolving nature of AI/ML technologies [19]. The study by Laishram and Thongam (2020) [20] aimed to detect and classify dental pathologies using the faster-R-CNN algorithm on orthopantomogram (OPG) radiography im-ages. The methodology likely involved training the faster-R-CNN model on a dataset of OPG images with labeled dental pathologies and evaluating its performance through detection and classification accuracy metrics.

With only one of the third molars, the maxillary fixed canines are the teeth that are impacted the most commonly. This condition is between 1.5% and 2.5% common [19]. The girls are between two and three times more likely than men to have canine im-paction, there may be a gender-dependent propensity. Maxillary canine impaction can be caused by a variety of factors. In addition to dental misalignment or a lack of available space, it is thought that the presence of hard and soft tissue diseases might obstruct the normal course of maxillary canine extrusion [20]. By removing the etiological cause, some independent restoration and spontaneously extrusion of impacted canines may be anticipated [21]. Gillot et al. (2022) [22] proposed an automatic segmentation approach for multi-anatomical skull structures in CBCT scans using 3D algorithm. The study likely entailed training the model on annotated CBCT datasets and evaluating its performance in accurately delineating skull structures. Challenges may include addressing variations in CBCT image quality and ensuring generalizability across different patient populations or imaging conditions.

Kim et al. (2023) explored the applications of AI in orthodontics. The frequency of canine impaction was higher with lateral incisors were completely absent, peg-shaped, or hypoplastic, suggesting a link between lateral incisor abnormalities and the condition [23]. These defects prevent the lateral incisors from properly guiding the growing canines, which causes their palatal displacement [23, 24]. The study likely reviewed various AI methods and their roles in orthodontic practices, such as diagnosis, treatment planning, and outcome prediction. The review probably assessed the effectiveness and challenges of implementing AI in orthodontic workflows. Limitations could involve the evolving nature of AI technologies and the need for further clinical validation [25]. The genetic view, in contrast, contends that a palatially relocated maxillary canine results from genetic reasons and that initial movement of the dental bud is solely inherited [26].

Research gaps in the field of AI-based auxiliary canine impactions refer to areas wherever added investigation is needed to improve the understanding and application of AI in diagnosing, managing, and treating cases of impacted canine teeth i.e., patient-specific predictive models, treatment planning and optimization, integration with dental imaging, and patient outcomes and long-term follow-up [27-30].

Hartsfield et al. (2022) [31] conducted an AI-based analysis on auxiliary canine impaction in orthodontics. The study likely utilized AI algorithms to analyze factors contributing to canine impaction and predict impaction risks. Methodology may have involved training AI models on datasets of orthodontic cases with and without canine impaction. Limitations might include the need for clinical validation of AI predictions and potential biases in the training data [31]. The length of the treatment process can be shortened by lowers the likelihood of problems or unfavorable results, and simplifies the mechanics of orthodontic therapy, early identification and interceptive dealing for maxillary canine impaction are essential. Reduced occurrence of crosswise, and occasionally central, pointed tooth root resorption is also very important. The permanent canines may spontaneously emerge after the deciduous canines are removed. If early care is not carried out, other problems might develop, including discomfort, infection, cyst development, ankylosis, internal or external degradation of the canine, and the neigh-boring teeth [32, 33].

The foundation of the present investigation was previously completed study [34]. Proposed a model for prediction based on three parameters: the canine cusp's perpendicular distances from the midline and the upper maxillary plane, as well as the angle be-tween the canine's cusp and the initial premolar [35, 36]. This method could distinguish between regular monitoring of canine impact and early intervention by detecting these three differentiating fac-tors [37, 38]. The primary goals of the present study are to create an innovative prediction model for maxillary canine impaction, leveraging a larger sample size. This model will be constructed based on various linear and angular measures extracted from panoramic radiographs. Additionally, the study aims to validate both the newly developed prediction model and existing models referenced in previous works [39, 40]. In the domain of canine impaction, prior studies have employed diverse approach-es, including local binary pattern (LBP) feature ex-traction, CNN, recurrent neural network (RNN), support vector machine (SVM), long short-term memory (LSTM)-based dynamic canine impaction analysis and cross-cultural analysis. Noteworthy challenges preceding the proposed work include the need for capturing and interpreting subtle, context-dependent impaction features [41, 42]. Additionally, there is a challenge in obtaining balanced datasets for training models, considering the variations pre-sent in canine images with different impaction characteristics. Jiménez-silva et al. (2022) [43] conducted a systematic review on prediction methods of maxillary canine impaction, revealing insights crucial for orthodontic treatment planning. An AI-based automated system for preprocessing and classifying impacted maxillary canines in panoramic radiographs, promising improved diagnostic efficiency in dentomaxillofacial radiology [44, 45].

The motivation for performing auxiliary canine impaction, also known as surgical exposure typically stems from dental and orthodontic needs of the patient. Here are some common motivations for pursuing this dental procedure orthodontic correction, aesthetics, functional improvement, prevention of complications, early intervention, alignment of the dental arch, comfort and functionality, overall oral health and patient satisfaction.

The final review on AI-based auxiliary canine impaction presents a comprehensive evaluation of recent advancements in using AI for diagnosing and managing impacted auxiliary canines. By synthesizing findings from multiple studies, it highlights the potential of AI in accurately predicting impaction, aiding treatment planning, and improving diagnostic efficiency in dentistry. This synthesis underscores the growing significance of AI applications in dental practice, paving the way for more precise and streamlined patient care in orthodontics and dentomaxillofacial radiology.

3.Materials and methods

3.1Dataset

The dataset for this study utilized 1973 digital panoramic x-rays generated by the SoredexCranexD digital panoramic x-ray device. The images are with a resolution of 2900 × 1250 pixels. No radiography records have been acquired for the intent of this investigation; All images were acquired for diagnostic and treatment planning purposes. To refine the sample size, exclusion criteria (It includes age of the patient, previous treatment undergone, systematic conditions, severe skeletal discrepancies and missing records) were applied before selecting two subsets from the original collection. Records related to implants were specifically excluded from consideration. Additionally, patients younger than 20 years old were not included in the dataset to guarantee that no deciduous teeth were visible in the photos and that the development of the jaw had nearly finished. Blurry or incorrectly positioned x-rays that were of poor-quality owing to a technician's or a patient's fault. *Table 1* shows the dataset descriptions.

Table 1 Dataset description

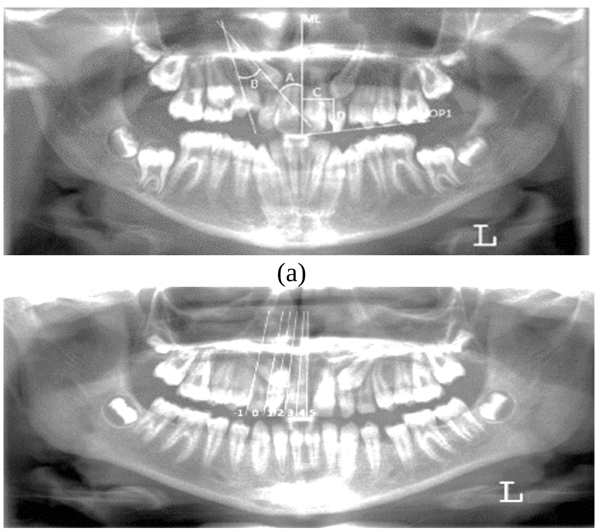
S. No.	Content	No.of images
1	Training Group (80%)	1578
2	Testing Group (17%)	336
3	Validation Group (5%)	59
Total number of images - 1973		

3.2Methodology proposed

Patients who have previously undergone orthodontic treatment, patients with craniofacial anomalies associated with/without eruption abnormalities patients with history of trauma and/or operation in the head and neck region and patients with musculoskeletal or bone disorders. Measurements and sector classification with the following parameter as shown in the *Figure 1 (a* and *b). Figure 1 (a)* shows the various measurements used for experimentation analysis and *Figure 1 (b)* shows the sector classification.

3.2.1Inclusion criteria:

Patients with unilateral/bilateral impacted maxillary canine, buccal /palatal canine impaction, retained /exfoliated deciduous maxillary canine with unerupted permanent maxillary canine, no age or gender restrictions.



(a)

(b)

Figure 1 (a) Measurements (b)Sector classification

3.2.2Exclusion criteria:

Patients who have previously undergone orthodontic treatment, with craniofacial anomalies associated with/without eruption abnormalities, with history of trauma and/or operation in the head and neck region and with musculoskeletal or bone disorders are excluded. Measurements and sector classification with the following parameter as shown in the *Figure 1* (a and b). *Figure 1 (a)* shows the various measurements used for experimentation analysis and *Figure 1 (b)* shows the sector classification.

- Maxillary dental mid line (MDL): Line passing through the anterior nasal spine through the interincisal contact of the permanent maxillary central incisors.
- Maxillary occlusal plane (MOP): Horizontal line connecting the incisal and occlusal surfaces of the permanent central incisor to permanent first molar on either side of the ML.
- Angle between lengthy axis of maxillary canine to the midline
- Angle between lengthy axis of maxillary canine to that of the adjacent incisor
- C - Angle between lengthy axis of maxillary canine to the occlusal plane
- D1- Vertical distance between maxillary canine tip to the occlusal plane
- D2- Vertical distance between maxillary canine tip to midline
- Sector lines are typically referred to the divisions or segments used to classify and analyze teeth and shown in *Figure 2.* These lines help dentists and dental professionals identify specific areas of a tooth for examination, diagnosis, and treatment planning and it is shown in the following figure. These sectors are named as 1. Quadrant lines 2. Sextant lines 3. Tooth surface lines 4. Root canal lines 5. Crown and tooth division.
- Canine tooth: Canine teeth, also known as cuspids or eyeteeth, are the pointed teeth located towards the corners of the dental arches, adjacent to the incisors. In both the upper and lower dental arches, there are four canine teeth, with two in each quadrant of the mouth. In dental care, canine teeth are subject to various dental issues, including cavities, fractures, and malocclusion (misalignment). Treatment for canine teeth may include dental fillings, crowns, orthodontic procedures, or even extraction in cases of severe damage or malpositioning. Canine teeth hold significance not only for their functional role in chewing but also for their contribution to the overall aesthetics and structural integrity of the dental arches.

The canine was considered to be impacted if the mean angulation of canine to MOP was 112.6° ± 19.4°. This angle was also used for Bucco palatal localization of impacted canine. Vertical distance be-tween the maxillary canine tip to the occlusal plane. It is measured by drawing a perpendicular line from the canine tip of the impacted occlusal plane to ca-nine. The main distinction of deep learning techniques is their capacity to study from a fresh data in-put, such as the pixels in a picture, without the need for manually engineered features.

One of the most well-liked collections of deep learning techniques is called deep CNNs, and it is frequently used for image identification jobs. In order to successfully represent and learn structural features using many levels of abstraction, CNN designs take advantage of unique aspects of an image data input, such as the spatial relationships between objects.

Figure 2 Sector lines

The *Figure 3* shows the block diagram of the projected methodology. X-Ray images are used as an input for the system presented here. The system then crops the X-ray based on the predicted bounding boxes. Based on the given coordinates ML, MOP line, sector lines and canine tooth are marked over the cropped image. The system outputs angle between Midline and canine, MOP line and canine and sector line and canine and to its tip to MOP and ML. It also gives the information that the canine lies in which sector. The system automatically predicts whether it is favorable for canine treatment. A fully-connected classification layer, two convolutional-pooling layers that follow one another. The two convolutional pooling layers each have 64 and 128 neurons, although they both utilize the same fixed 8 8 convolutional kernel and 2×2 pooling kernel. The 256 neurons in the last layer are all connected to the two remaining neurons that determine whether a cell is in mitosis or not [42].

3.2.3Image pre-processing:

The proposed model is implemented using Python. In the initial phase, we reduced the size of all photos to 100×100 pixels to optimize the data for model training using pre-processing and cropping algorithm:

Step 1: The cropping algorithm aims to select a rectangular or arbitrary-shaped region from the original image and create a new image containing only the selected region.

- Input: Loading original image
- Selecting region of interest (RoI): Determine the RoI in an image that you want to keep. This could be done manually by specifying the coordinates specifying the locations of the bottom-right and top-left. of the rectangular region or by using any other method to define the region (e.g., drawing a polygon around the region).

Step 2: Cropping:

- Extract the pixels from the original image corresponding to the selected ROI.
- Create a new image using the extracted pixels.
- The cropped image, containing only the RoI.

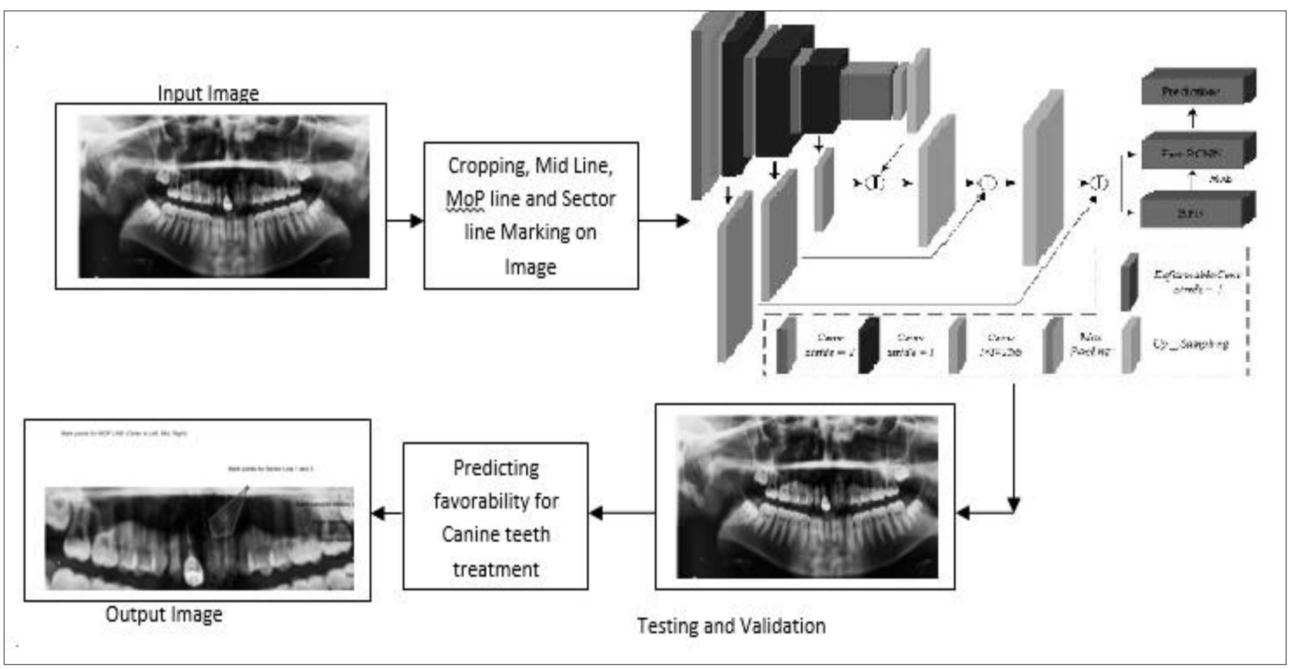


Figure 3 Architecture Diagram of Proposed Work

Figure 4 displays the input image, while *Figure 5 (a)* and *(b)* depict the pre-processed image and the cropped image, respectively.

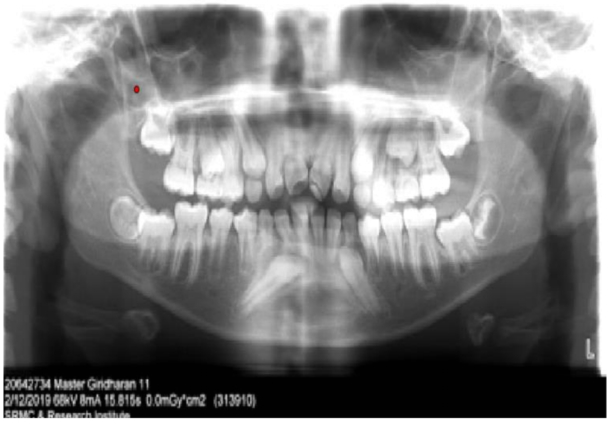
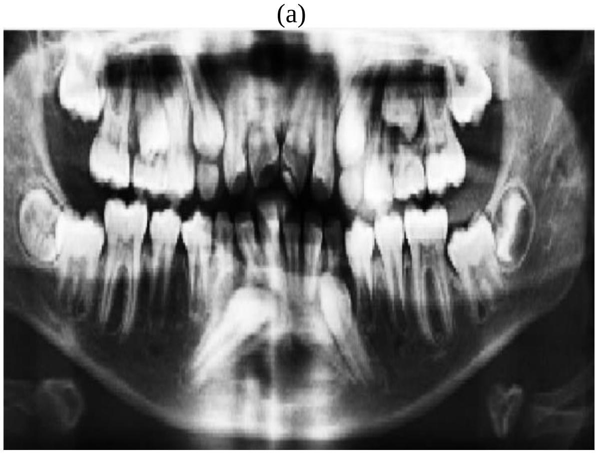


Figure 4 Input image

(a)



(b)

Figure 5 (a) Pre-processed Image (b) Cropped Image

3.2.4Drawing sector lines:

Automatically drawn sector lines on the cropped image by using image coordinates by satisfying the sector line rules. *Figure 6* shows the canine image with sector lines.

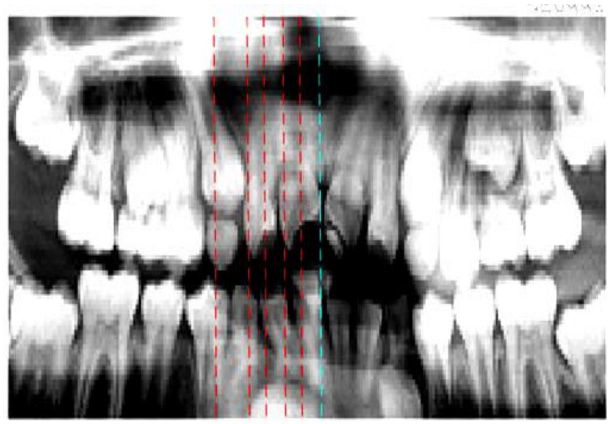


Figure 6 Image with sector lines

3.2.5Detection of canine teeth:

The proposed work used drawpolygon() function to highlight the canine teeth on the image. This data will be utilized to compute the ideals of A, B, C, D1 and D2. All the canine teeth will be identified using this method. *Figure 7* shows that canine teeth detection on X-Ray image, finding A, B, C, D1 and D2 for an input image. The above values are detected automatically and stored in the datasheet. *Figure 8* shows the final out-put of the proposed work.

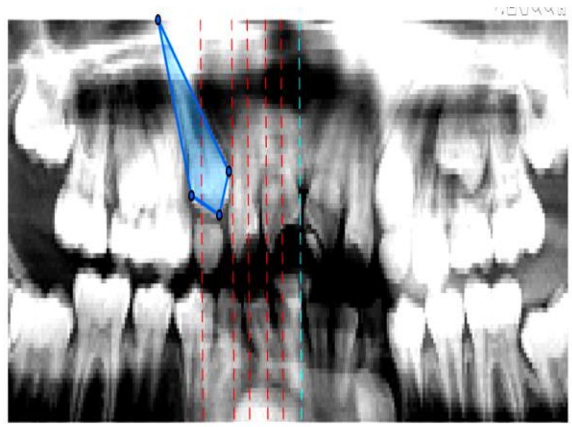


Figure 7 Image with highlighted canine tooth

The same process has been applied for all the images in the dataset and those records are maintained in the datasheet for training purpose. The following favorability for prediction is added in the datasheet.

'A' – value should be <=31˚

'B' – Value should between 15.1˚ and 51.4˚

'C' – Value should between 93.2˚ and 132˚

The proposed work also finds that the canine teeth fall on which sector to predict the favorability.

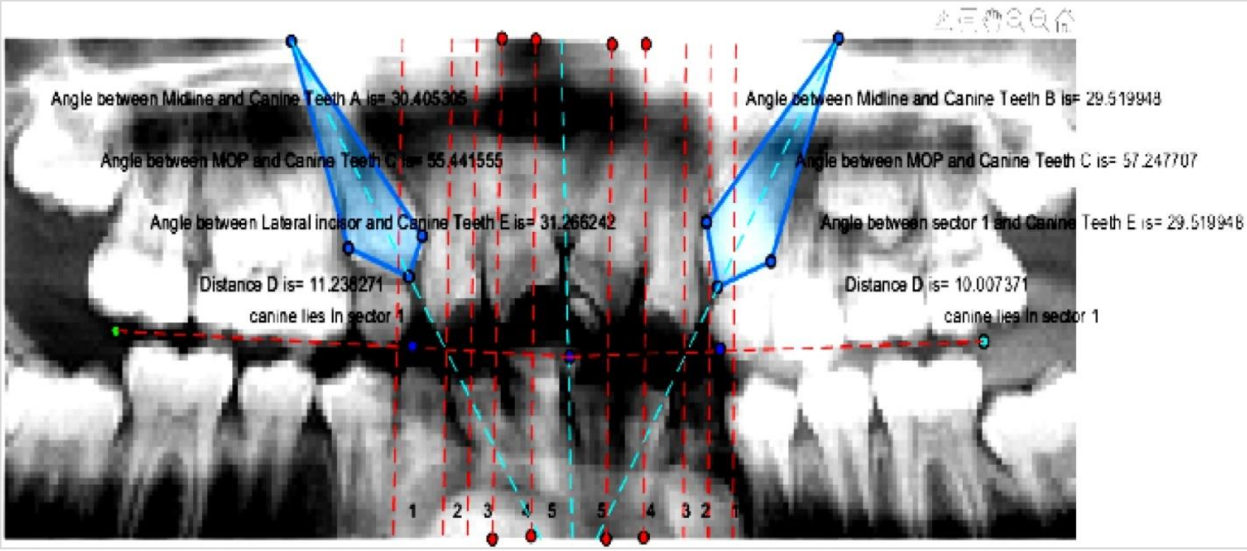


Figure 8 Final output with prediction

3.2.6Fast-R CNN algorithm for training and test-ing:

Fast R-CNN could assist in identifying and precisely localizing impacted maxillary canines within radiographic images, such as panoramic radiographs or CBCT scans. By automating this process, fast R-CNN could significantly reduce the time and effort required for manual examination by orthodontists and radiologists, leading to more efficient diagnosis and treatment planning.

Furthermore, the consistent and objective analysis provided by fast R-CNN may enhance the reliability of impaction detection, enabling earlier intervention and improving treatment outcomes. Integrating fast R-CNN into the clinical workflow could streamline the detection process, allowing for seam-less communication between orthodontists and radiologists and facilitating timely patient care.

In the context of maxillary canine impaction, a CNN will be used for an image analysis and prediction jobs related to diagnosing and forecasting the incidence of it. A CNN can take dental radiographic images (e.g., panoramic or periapical X-rays) as in-put and learn to classify them into impacted or non-impacted categories. Here's a general outline of the mathematical model for a CNN algorithm in maxillary canine impaction:

Step 1: Data representation:

Input images: Dental radiographic images of patients' maxillary canines.

Labels: Binary labels indicating whether the maxillary canine is impacted or not (e.g., 0 for non-impacted, 1 for impacted).

Step 2: Convolutional layers:

For every convolutional layer, the operation follows the previously outlined description:

- Input: Represented by $X \in \mathbb{R}^{(H\times W\times C)}$, where H is the image height, W is the image width, and C is the number of channels (e.g., grayscale = 1, RGB = 3).
- Filters: Denoted by $K_i \in \mathbb{R}^{(k_i\times k_i\times C_i)}$, where k_i signifies the size of the ith filter, and C_i represents the number of input channels for the ith layer.
- Output Feature Map: Expressed as $O_i \in \mathbb{R}^{((H_i-k_i+1)\times(W_i-k_i+1)\times N_i)}$, where H_i, W_i, and N_i denote the height, width, and number of filters for the ith layer, respectively.

Step 3: Activation Function:

Following each convolutional layer, a non-linear activation function, such as rectified linear unit (ReLU), is applied element-wise to introduce non-linearity:

$O_i = \sigma(O_{i\_raw}) = \max(0, O_{i\_raw})$

Step 4: Pooling Layers:

To downsize spatial dimensions while preserving crucial features, the common practice involves employing either max pooling or average pooling:

- Input: $O_i \in \mathbb{R}^{((H_i\times W_i\times N_i))}$.
- Output: $P_i \in \mathbb{R}^{((H_i/2)\times(W_i/2)\times N_i)}$, where the pooling operation reduces height and width by half.

Step 5: Fully Connected Layers:

The result of the final pooling layer is transformed into a flattened vector, which is then propagated through fully connected layers:

- Input: $FC_{in} \in \mathbb{R}^{(D)}$, where D is the number of neurons after flattening the last pooling layer.

- Weight matrix: W_FC ∈ ℝ^(D×M), where M is the number of neurons in the fully connected layer.
- Bias vector: b_FC∈ ℝ^M.
- Output: FC_out∈ ℝ^M.

Step 6: Output Layer (Classification):
- The outcome of the ultimate fully connected layer undergoes a sigmoid activation function, generating the probability associated with the maxillary canine being impacted.
- Input: FC_out∈ ℝ^M.
- Output (Probability): P_impact = σ(FC_out)

Step 7: Loss Function:
Throughout the training process, an appropriate loss function, such as binary cross-entropy, is employed to quantify the disparity between the predicted probabilities and the actual ground truth labels.
Step 8: Optimization:
A stochastic gradient descent, is used to iteratively apprise the model's constraints during training. The objective is to curtail the loss function, refining the model's predictive accuracy over successive iterations.

4.Results

Python is used to provide the experimental simulations tool, and simulations conducted on a diver image are used to verify the technique's feasibility. Windows'10 (Intel core i7 processor) with 16GB RAM and 4GB hard disk drive (HDD). In the initial phase the image was reduced to 100×100 pixels to optimize the data for model training. Then, using the associated landmarks from each training image, whole target dataset has been trained. In a nutshell, the deep CNN model used to build the proposed model in stages. The group size is 1923, the learning rate is 0.01, and there are150 epochs in the image during the training phase. The trained model recognized the favorability in the test photos automatically.

4.1Quality measures:

The evaluation metrics employed encompass sensitivity, accuracy, and precision, denoted by Equations 1 to 3. These metrics are computed based on parameters: false negative (FN), true negative (TN), true positive (TP) and false positive (FP). Precision gauges the relevance of the algorithm's performance, indicating the proportion of accurately identified instances among those flagged as positive. Recall, conversely, quantifies the ratio of correct classifications made by the algorithm concerning the total occurrences of functional outcomes. This complete metrics offers a thorough assessment of the algorithm's recital across various dimensions, ensuring a nuanced understanding of its efficacy (Equation 1 to 3).

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Precision = \frac{TP}{FP+TP} \quad (3)$$

4.2Discussions

The proposed method with fast R-CNN achieved precision, sensitivity and accuracy of 96.8, 96.5 and 98.3 respectively. It is shown in *Table 2* and *Figure 9.* The statistical analysis of maxillary canine impaction calculated using python and it has achieved 100 % accuracy by predicting the favorability of treatment is possible or not. *Figure 10* also shows that the proposed method achieved 98.3% accuracy. *Figure 10* shows the comparative analysis of the proposed work with the existing AI based techniques like VGG16, VGG18, EfficientNET84, ResNET with CNN and DenseNet with CNN. The comparison shows that the proposed work outperforms with the 98.3% of accuracy.

Table 2 Performance analysis for automatic detection of canine using fast R-CNN

Performance analysis parameters	Proposed system
Total number of images	1973
True positives	1940
False negatives	70
False positives	68
Precision	96.8 %
Sensitivity	96.5 %
Accuracy	98.3 %

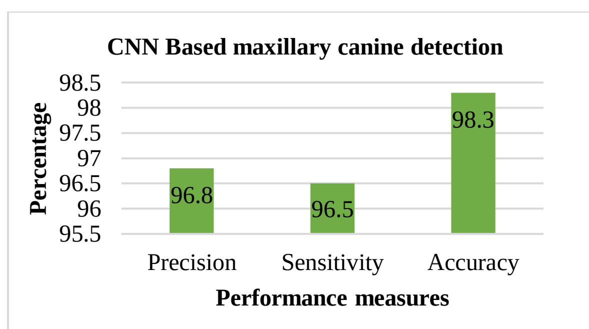


Figure 9 Performance analysis for automatic detection of canine using fast R-CNN

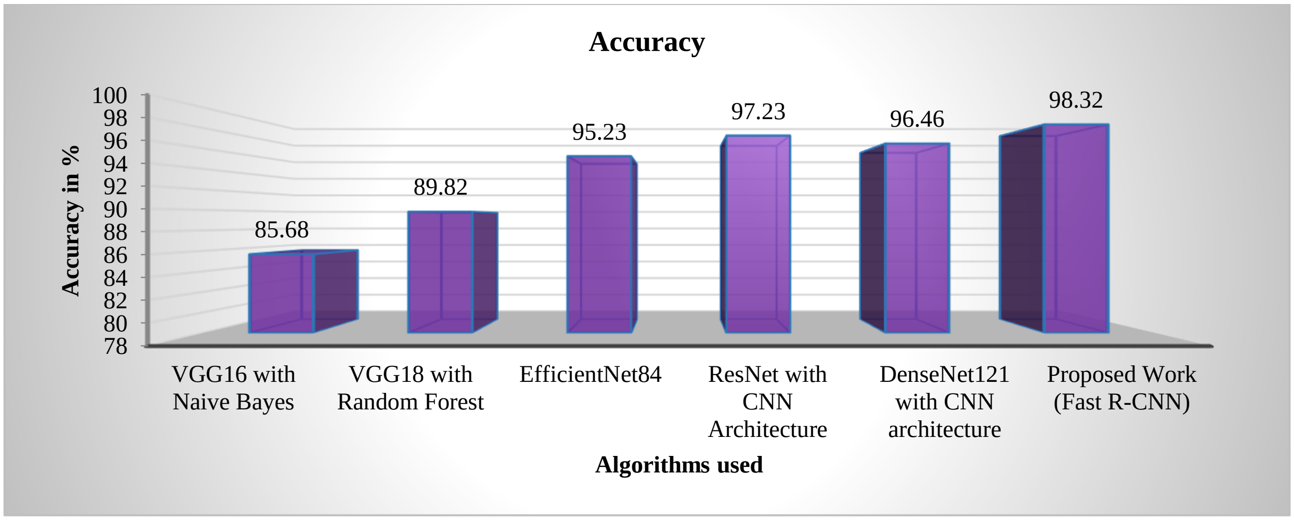


Figure 10 Comparative analysis of proposed method with existing algorithms [4]

The proposed method achieved 98.3 % of accuracy, when compared to statistical analysis shown in *Table 3*. NF indicates "Not Favourable," and F indicates "Favourable." The automatic maxillary canine impaction using CNN outperformed without manual intervention and less execution time. Since medical field getting more amount in day-to-day life, it is not possible to analyze all the data manually or statistical analysis, so the proposed method replaces all existing techniques with better accuracy in predicting maxillary canine impaction treatment possible or not.

Auxiliary canine impaction, the process involves the surgical exposure and subsequent orthodontic alignment of impacted canines, is a valuable procedure for addressing various dental and orthodontic issues. However, like any medical or dental procedure, it has its limitations and potential challenges in patient cooperation, age of patient, complexity of impaction, surgical risks, root resorption, duration of treatment, cost of treatment, and not suitable for all cases. Fast R-CNN consists of several stages, including region proposal generation, feature extraction, and region-based classification, each of which contributes to the overall computational cost and execution time. The computational requirements primarily depend on factors such as the complexity of the model architecture, input image size, batch size, and hardware acceleration. The proposed method has executed in 3.55 minutes which is very less compared to manual process in real-world ap-plication.

4.3Limitations:

Using fast R-CNN for identifying maxillary canine impaction presents several limitations. Medical images such as X-rays or CT scans may vary widely in quality, potentially impacting the model's performance, especially in cases of low resolution or arti-facts. Interpretability remains a challenge, as deep learning models often operate as black boxes, com-plicating the understanding of the reasoning behind predictions. Moreover, the model's reliance on two dimensional (2D) images may not fully capture the complexities of 3D anatomical structures, potentially leading to inaccuracies, particularly in cases of subtle impaction or complex anatomical contexts. FP's and FN's are also concerns, potentially leading to misdiagnosis or oversight of impaction cases. Integration into clinical workflows requires expertise in both deep learning and the medical domain, and regulatory approval may be necessary, further com-plicating implementation. Overall, while fast R-CNN offers promise for impaction detection, these limitations indicate the need for cautious interpretation and further research to ensure its clinical utility. A complete list of abbreviations is listed in *Appendix I*.

Table 3 Statistical analysis for detection of canine

S. No.	A	FAVORABILITY	C	FAVORABILITY	B	D1	D2	SECTOR	FAVORABILITY
1	37	NF	136	NF	39	21	5	4	NF
2	57	NF	154	-	60	12	12	3	NF
3	16	F	117	F	27	14	22	1	F
4	19	F	112	F	31	17	19	2	F

S. No.	A	FAVORABILITY	C	FAVORABILITY	B	D1	D2	SECTOR	FAVORABILITY
5	13	F	109	F	15	9	21	1	F
6	8	F	136	F	8	9	22	1	F
7	37	NF	154	NF	39	21	5	4	NF
8	57	NF	117	-	60	12	12	3	NF
9	16	F	112	F	27	14	22	1	F
10	19	F	109	F	31	17	19	2	F
11	13	F	136	F	15	9	21	1	F
12	8	F	154	F	8	9	22	1	F
13	37	NF	117	NF	39	21	5	4	NF
14	57	NF	112	-	60	12	12	3	NF
15	16	F	109	F	27	14	22	1	F
16	19	F	136	F	31	17	19	2	F

5.Conclusion and future work

The CNN application for automatic maxillary ca-nine impaction prediction holds significant promise in the field of dentistry and orthodontics. This study explored the feasibility of utilizing CNNs to analyze dental radiographic images and predict the occurrence of maxillary canine impaction with high accuracy. Through the implementation of a carefully de-signed R-CNN architecture and the use of a diverse and well-curated dataset, this model demonstrated robust performance in distinguishing between impacted and non-impacted cases. The results show-cased impressive values for accuracy, precision, and sensitivity indicating the model's ability to effectively identify potential canine impactions. This implies that leveraging the R-CNN-based methodology holds promise as a valuable resource for aiding dental practitioners in the timely identification and planning of treatments for individuals grappling with maxillary canine impaction. The current study achieved 98.3% of accuracy, this adds to the expanding pool of evidence affirming the viability and precision of utilizing CNN-based automated predictions for maxillary canine impaction, underscoring its potential significance in clinical applications. As this technology continues to evolve, the findings of this study suggest that there is considerable potential for this approach to enhance the skills of dental professionals, streamline early detection processes, and ultimately enhance patient outcomes in the management of this prevalent dental condition. Yet, it indicates the importance of fostering collaboration among AI experts, dental specialists, and regulatory authorities. This collaboration is pivotal to guaran-tee the responsible and effective integration of this technology into clinical workflows, ensuring its seamless incorporation with ethical considerations and optimal effectiveness. By considering these do-mains, upcoming study can enhance the effective-ness, practicality, and reliability of R-CNN based automatic maxillary canine impaction prediction systems, ultimately improving patient care and treatment outcomes in dental and orthodontic practice.

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None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The dataset for this study utilized 1,973 digital panoramic x-rays generated by the Soredex Cranex D digital panoramic x-ray device, with a resolution of 2900 × 1250 pixels. No radiography records were acquired specifically for this investigation; all images were acquired for diagnostic and treatment planning purposes. The dataset is not publicly available.

Author contribution statement

S.Deepa: Contributed implementation of the proposed work and result and analysis part. **A.Umamageswari:** Contributed paper structuring and implementation work, **L.Sherinbeevi:** contributed literature survey and introduction part. **A.Sangari**: Contributed dataset collection and overall structuring of paper.

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Dr. S.Deepa is currently working as an Assistant Professor in the Department of Computer Science and Engineering at SRM Institute of Science and Technology, Chennai. She received her BE in Computer Science and Engineering from Sri Venkateswara College of Engineering and Technology, Madras University, her ME in Computer Science and Engineering from Jaya Engineering College, Anna University, and her PhD from the College of Engineering, Anna University. She has 14 years of teaching experience and she has published more than 25 papers inreputed journals and conferences. She is an active member in ISTE. Her research interest includeImage processing and Pattern Recognition.She also hosted many FDP, workshop and seminar andkey role in accreditation activities.
Email: deepas1@srmist.edu.in

Dr. A.Umamageswari is an Associate Professor and Deputy Head of the Department for Big Data Analytics at SRM Institute of Science and Technology, Ramapuram Campus. She has over 20 years of academic experience. She completed her Ph.D. in Computer Science and Engineering with a focus on Medical Image Processing and her M.Tech at Sathyabama University, Chennai. She earned her B.E. in Computer Science and Engineering from Sri Venkateswara College of Engineering, Sriperumbudur, University of Madras. As a Research Supervisor at the SRM Institute of Science and Technology, she has published over 40 research papers in SCI, Scopus, and UGC Care Journals and authored two books in the Computer Science domain. She has organized and actively participated as a core member in numerous international and national guest lectures, Faculty Development Programs, and conferences. She holds two patents, is a member of several Boards of Studies, and belongs to professional organizations such as IEEE, ACM, ISTE, CSTA, and IAENG. She has received numerous awards, including the "Tamil Nadu Chief Minister's Medal." Under her leadership, the institute successfully underwent its first NBA—National Board of Accreditation cycle in 2018 and achieved accreditation status for three years.
Email: r.umaramesh@gmail.com

L.Sherinbeevi is an Assistant Professor in the Department of Computer Science and Engineering at R.M.D. Engineering College, Kavaraipettai. She completed her B.Tech in Information Technology in 2007 from St. Xavier's Catholic College of Engineering, Nagercoil, and her M.Tech in Computer Science and Engineering in 2009 from Francis Xavier College of Engineering, Tirunelveli, affiliated with Anna University, Chennai. Currently, she is pursuing a PhD in Blockchain with Quantum Computing at Anna University, MIT Campus, Chennai. With over 13.5 years in the teaching

profession, she has experience in both undergraduate and postgraduate programs. Her research interests include Computer Networks, Blockchain, Quantum Computing, Data Science, and Deep Learning. She has presented over 15 papers at various conferences and published more than 15 papers in various journals.
Email: sherinbeevi@gmail.com

A.Sangari is an Assistant Professor in the Department of Electrical and Electronics Engineering at Rajalakshmi Engineering College. She completed her undergraduate studies at Sri Venkateswara College of Engineering, Sriperumbudur, Chennai, and both her postgraduate degree and PhD in the area of Power Electronics at Rajalakshmi Engineering College, Anna University, Chennai. Her research focuses on Multi-Level Inverters, Z-Source Inverters, and Renewable Energy. She has published five research papers in refereed journals and presented at five international and four national conferences.
Email: sangari.a@rajalakshmi.edu.in

Appendix I

S. No.	Abbreviation	Description
1	2D	Two-Dimensional
2	3D	Three-Dimensional
3	AI	Artificial Intelligence
4	CBCT	Cone-Beam Computed Tomography
5	CNN	Convolutional Neural Networks
6	CT	Computed Tomography
7	R-CNN	Region Based Convolutional Neural Networks
8	FP	False Positive
9	FN	False Negative
10	HDD	Hard Disk Drive
11	LSTM	Long Short-Term Memory
12	MDL	Maxillary Dental Mid Line
13	MOP	Maxillary Occlusal Plane
14	OPG	Orthopantomogram
15	RNN	Recurrent Neural Network
16	ReLU	Rectified Linear Unit
17	ROI	Region of Interest
18	SVM	Support Vector Machine
19	TN	True Negative
20	TP	True Positive
21	VGG	Visual Geometry Group
22	XAS	Age and Sex
23	ML	Machine Learning
24	LBP	Local Binary Pattern