RESEARCH ARTICLE

DOI: 10.54392/irjmt2425

Asian Research Association

INTERNATIONAL RESEARCH JOURNAL OF
MULTIDISCIPLINARY TECHNOVATION

Enhancing Airway Assessment with a Secure Hybrid Network-Blockchain System for CT & CBCT Image Evaluation

Vamsi Krishna Uppalapati [a], G. Srinivasa Rao [b], Lavanya Addepalli [c], M. Bhavsingh [d, *], SD. Vidya Sagar [e], Jaime Lloret Mauri [c]

[a] Tata Main Hospital, Jamshedpur-831001, Jharkhand, India

[b] Department of Computer Science and Engineering, KL University, Guntur-522302, Andhra Pradesh, India

[c] Department of Communications, Universidad Politécnica De Valencia, Algirós, 4602, Spain

[d] Department of Computer Science and Engineering, Ashoka Women's Engineering College, Andhra Pradesh-518218, India

[e] Department of MCA, Nitte Meenakshi Institute of Technology, Bengaluru-560064, India

*Corresponding Author Email: bhavsinghit@gmail.com

DOI: https://doi.org/10.54392/irjmt2425

Received: 29-09-2023; Revised: 07-02-2024; Accepted: 13-02-2024; Published: 17-02-2024

Abstract: Our investigation explored the intricacies of airway evaluation through Cone-Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. By employing innovative data augmentation strategies, we expanded our dataset significantly, enabling a more comprehensive analysis of airway characteristics. The utility of these techniques was evident in their ability to yield a diverse array of synthetic images, each representing different airway scenarios with high fidelity. A notable outcome of our study was the effective categorization of the initial image as "Class II" under the Mallampati Classification system. The augmented images further enhanced our understanding by exhibiting a spectrum of airway parameters. Moreover, our approach included training a Recurrent Neural Network (RNN) model on a dataset of CT images. This model, fortified with pseudo-labels created via K-means clustering, showcased its proficiency by accurately predicting airway assessment categories in various test scenarios. These results underscore the model's potential as a tool for swift and precise airway evaluation in clinical settings, marking a significant advancement in medical imaging technologies.

Keywords: Airway Assessment, CBCT Images, CT Images, Data Augmentation, Mallampati Classification, RNN (Recurrent Neural Network), K-means Clustering, Machine Learning, Image Preprocessing, Airway Evaluation.

1. Introduction

Airway evaluation is an essential component of contemporary healthcare, with implications for various medical disciplines, including pulmonology, otolaryngology, critical care, and anaesthesia. The assessment of the structure and openness of the airway is of utmost importance in the identification and treatment of respiratory conditions, the preparation and execution of surgical procedures, and maintaining patient well-being during medical interventions [1]. There has been a notable emergence of medical imaging techniques, including Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) scans. These techniques have proven highly effective in providing non-invasive and comprehensive visualization of airway anatomy [2, 3].

The importance of airway assessment utilizing medical imaging cannot be overemphasized. Clinicians can effectively identify and measure airway abnormalities, detect pathological conditions, and develop individualized treatment strategies through this technology [4]. In the case of obstructive sleep apnea, accurate assessments of airway dimensions derived from CBCT or CT scans play a critical role in evaluating the extent of the condition and informing the choice of suitable treatment approaches, such as mandibular advancement devices or surgical interventions [5, 6].

Although there are potential benefits, current methods for evaluating airway assessment using CBCT and CT images have certain limitations. Conventional approaches in image analysis heavily depend on manual measurements, which introduces subjectivity and variability among different observers [7, 8]. Furthermore, the storage and dissemination of medical imaging data give rise to apprehensions regarding the security of data and the privacy of patients. In the current era characterized by an increasing focus on safeguarding data, it has become crucial to prioritize preserving the accuracy and secrecy of delicate medical data [9,10].

To address these challenges, this study presents a novel hybrid network-blockchain methodology to augment the security and precision of airway assessment by utilizing both CBCT and CT images. There are two main reasons for choosing to implement this approach. Our primary objective is to utilize advanced deep-learning techniques to create image evaluation models that are both reliable and automated. These models can accurately assess airway dimensions, identify abnormalities, and categorize pathologies with minimal human involvement. This will result in a reduction of potential errors and an improvement in diagnostic accuracy.

The research presented in this study is distinguished by the development and application of an innovative hybrid network-blockchain methodology for evaluating airways through the utilization of medical imaging techniques, specifically Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. The proposed system seamlessly integrates precise and automated airway analysis by integrating advanced deep-learning models for image evaluation with a data security mechanism based on blockchain technology. This integration also guarantees patient data integrity, confidentiality, and traceability. Integrating advanced technologies in this novel approach aims to overcome the constraints associated with conventional manual techniques. Consequently, it facilitates more accurate diagnoses, optimizes clinical processes, and enhances the quality of care provided to patients in diverse medical disciplines that heavily rely on airway assessment.

The key insights of the research are:

1. **Data Augmentation**: Successfully expanded dataset with diverse synthetic images for airway analysis.
2. **Classification Accuracy**: Initial image classified as "Class II" in Mallampati Classification; augmented images showed varied airway parameters.
3. **RNN Model**: Developed and trained on CT images with pseudo-labels from K-means clustering.
4. **Effective Predictions**: RNN model accurately predicted airway assessment categories in tests.
5. **Clinical Utility**: Demonstrated potential for rapid, accurate airway evaluation in clinical settings.

Utilizing blockchain technology offers a decentralized and tamper-resistant framework to secure and manage medical image data along with decentralized ledger system guarantees the comprehensive documentation of every transaction or instance of patient data access, thereby promoting transparency and immutability [11]. This feature enhances data integrity and serves as a deterrent against unauthorized access. This engenders a sense of assurance in patients and healthcare professionals, while also acknowledging the escalating apprehensions about data breaches and infringements on privacy.

Our proposed hybrid network-blockchain approach seeks to revolutionize airway assessment in healthcare by integrating deep learning models and blockchain technology. This study aims to enhance patient care, optimize clinical workflows, and enhance diagnostic accuracy across diverse medical disciplines by addressing the shortcomings associated with conventional approaches.

The remainder of this paper is organized as follows: Section 2 reviews related work in the fields of airway assessment, deep learning, and blockchain technology. Section 3 details our methodology, including the design of the deep learning models and the blockchain system. Section 4 presents the experimental setup, results, and discussion of our findings. Section 5 explores the potential implications of our work and future research directions. Finally, Section 6 concludes the paper with a summary of our contributions and findings.

2. Related Work

The literature review section of this research paper provides a comprehensive examination of the current methodologies employed in evaluating airway conditions using Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. This review thoroughly analyses the existing literature to investigate the various methodologies utilized in assessing airway conditions. This encompasses an exploration of deep learning techniques as well as the implementation of blockchain solutions. By critically comparing these methodologies, we aim to identify and analyze their respective strengths, limitations, and potential implications in medical imaging and diagnostics. Moreover, this review aims to identify significant deficiencies in the existing body of literature, thereby creating an opportunity to introduce a groundbreaking hybrid network-blockchain methodology to effectively address these limitations in the evaluation of both Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. The proposed methodology combines advanced deep learning algorithms with the security and integrity offered by blockchain technology. This integration presents a novel and promising opportunity to improve airway assessment's precision, dependability, and confidentiality in the healthcare sector.

2.1 CBCT & CT Imaging

The literature review section of this research paper provides a thorough and inclusive examination of the current corpus of knowledge about airway evaluation using Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) imaging. The reviewed literature emphasizes the importance of precise modelling and quantification of the upper pharyngeal and nasal airways in diverse medical contexts. Multiple studies have underscored the enhanced imaging capabilities and comparatively reduced radiation dosage of cone-beam computed tomography (CBCT) concerning multi-detector computed tomography (CT), thereby establishing its significance as a valuable modality for assessing upper airway structures [12]. Furthermore, the review examines the reliability of assessments based on Cone Beam Computed Tomography (CBCT), emphasizing the significance of employing standardized imaging protocols and segmentation methods to attain consistent and accurate outcomes. In addition, this study investigates the significance of cone-beam computed tomography (CBCT) in diagnosing dental-maxillofacial conditions and its potential utilization in various clinical domains such as orthodontics, sleep apnea, and surgical planning [13,14]. The amalgamation of these investigations enhances comprehension regarding the present condition of airway evaluation by utilizing CBCT and CT imaging. The statement above underscores the necessity for additional research to enhance standardization and reliability within medical imaging, which holds significant importance.

El Khateeb, S. (2020) review article comprehensively examines various methodologies employed in segmenting three-dimensional images obtained through cone-beam computed tomography (CBCT) to evaluate the human upper airway. The authors emphasize the precision, effectiveness, and comparatively reduced radiation exposure of cone-beam computed tomography (CBCT) compared to multi-detector computed tomography (CT). The review underscores the significance of precise modelling of the upper airway to enhance the diagnosis process, treatment planning, and evaluation of treatment outcomes [15].

The systematic review by Zimmerman, & Pliska, (2016) aims to assess the reliability of dental cone-beam computed tomography (CBCT) in evaluating the upper pharyngeal airway. The authors extensively searched various databases and evaluated the methodological rigour of the included studies. The analysis reveals that within specific limited parameters, a substantial degree of consistency and agreement among examiners in evaluating the upper airway through the utilization of cone-beam computed tomography (CBCT). Additionally, it underscores the significance of considering airway volume during the evaluation [16].

The research paper by Mupparapu, Shi, Setzer, (2021) introduces a novel approach to segment and quantify the nasal airway utilizing cone-beam computed tomography (CBCT) to enhance the accuracy and precision of volumetric evaluation. The authors examine the ITK-SNAP software as a tool for delineating anatomically precise boundaries of the nasal airway. The primary objective of this study is to establish a standardized approach to segmentation, thereby facilitating improved comparability across various studies. The validation process involves segmenting CBCT samples obtained from healthy patients [17].

The primary subject of the review article by Deivanayagi, M., *et al* (2021) is the utilization of oral and maxillofacial imaging techniques, particularly cone beam computed tomography (CBCT), for assessing the upper airway. The authors emphasize the constraints associated with two-dimensional imaging techniques and underscore the benefits of cone beam computed tomography (CBCT) in delivering enhanced imaging capabilities for dental-maxillofacial diagnostic purposes. The significance of a thorough evaluation encompassing clinical examination, radiographic assessment, and cone-beam computed tomography (CBCT) is underscored in the review. This comprehensive approach is crucial in identifying functional alterations that may have implications for treatment [18].

The objective of the systematic review by Gurani, Sirwan Fernandez, *et al*. (2016) is to examine the impact of head and tongue posture on the dimensions and morphology of the pharyngeal airway using three-dimensional imaging techniques such as computed tomography (CT), cone-beam computed tomography (CBCT), and magnetic resonance imaging (MRI). This study aims to assess the impact of altering posture from the natural head position on the dimensions and morphology of the pharyngeal airway during imaging acquisition. The review encompasses a comprehensive and methodical examination of relevant scholarly articles obtained through a systematic search of the PubMed, Embase, and Cochrane databases. This rigorous process yielded four publications that met the inclusion criteria. The assessment of study quality indicated that a significant proportion of the studies evaluated were of poor quality and provided low-level evidence, accounting for 46-67% of the maximum attainable score. Due to a heterogeneous methodology, the execution of a meta-analysis was rendered unfeasible, leading to the adoption of a narrative synthesis approach instead. The review's findings indicate that the existing literature on the impact of head and tongue posture on pharyngeal airway dimensions and morphology in three-dimensional imaging is characterized by a scarcity of evidence, poor quality of studies, and a lack of high-level research. Nevertheless, the research emphasizes the significance of maintaining the natural head position during imaging acquisition to achieve standardization. Additional investigation is required to enhance these evaluation techniques' dependability and uniformity [19].

The study conducted by Guijarro-Martínez & Swennen, (2011) in the systematic review to assess the utility of cone-beam computed tomography (CBCT) in evaluating the airway. The researchers performed an extensive search across various databases and evaluated the methodological rigour of the studies that were included in the analysis. The review concludes that Cone Beam Computed Tomography (CBCT) is a dependable and precise technique for evaluating the airway, exhibiting strong consistency among examiners within and between them. The authors emphasize the significance of establishing standardized imaging protocols and segmentation methods to achieve precise and dependable airway evaluation. The review additionally examines the potential clinical uses of cone-beam computed tomography (CBCT) in evaluating the airway, encompassing areas such as orthodontic treatment planning, diagnosis of sleep apnea, and surgical planning [20].

As previously stated, the articles offer a thorough examination of the present status of research about airway assessment utilizing CBCT and CT images. The research emphasizes the significance of precise segmentation, dependable volumetric evaluation, and thorough upper airway assessment. The authors highlight the benefits of cone-beam computed tomography (CBCT) in offering enhanced imaging capabilities for the diagnosis and treatment planning of airway-related disorders. Nevertheless, it is imperative to conduct additional research to enhance these evaluation techniques' dependability and uniformity.

2.2 Deep Learning & Blockchain Technologies

The literature review section of this research paper provides an extensive examination and juxtaposition of diverse deep-learning methodologies and blockchain-based solutions implemented within the domain of airway assessment. Recently, incorporating deep learning algorithms has brought about a significant transformation in medical imaging. This integration has facilitated the automated and precise analysis of intricate anatomical structures. This review provides a critical analysis of the current body of literature to identify the various deep learning models employed for airway assessment using medical imaging techniques, specifically Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT). Furthermore, the present review investigates the nascent implementations of blockchain technology in medical imaging to augment the safeguarding of data security, privacy, and integrity in the context of airway evaluation. This review seeks to analyze and assess contemporary methodologies to comprehensively understand the advantages, drawbacks, and potential consequences of incorporating deep learning and blockchain solutions into airway assessment. The objective is to offer valuable guidance for future research endeavours and the practical integration of these technologies in the crucial healthcare domain. Deep learning techniques and blockchain solutions have been utilized in diverse domains, encompassing the assessment of airway functionality. This paper presents a comprehensive analysis and comparative examination of various studies that have employed these technologies within the specified field.

Patan, & Parizi, (2022) discusses the performance Improvement of Blockchain-based IoT Applications using Deep Learning Techniques. *2022 Fourth International Conference on Blockchain Computing and Applications (BCCA)*, 151-158.The authors of the study proposed a model called DeepIoT-Block to effectively tackle the security concerns related to storage in Internet of Things (IoT) applications. The proposed approach integrates the consensual deep learning (CDL) methodology with the elliptic Diffie-Hellman protocol to enhance the effectiveness of the blockchain-based data storage scheme (BDSS). Additionally, the Directed Acyclic Graph (DAG) is employed to establish the underlying structure of the blockchain network. The efficacy of the proposed model was assessed and confirmed for the utilization of IoT-based smart road traffic data. The simulation results demonstrate that DeepIoT-Block exhibits computational efficiency and security when applied to larger-scale IoT applications [21].

Joshy & Rajan, (2022) investigation was undertaken to categorize the levels of dysarthria severity by utilizing various deep-learning methodologies and acoustic characteristics. The present study assessed fundamental architectural options, including deep neural network (DNN), convolutional neural network, gated recurrent units, and extended short-term memory network. These options were evaluated using basic speech features, specifically Mel-frequency cepstral coefficients (MFCCs) and constant-Q cepstral coefficients. The investigation also examined the efficacy of employing subspace modelling to generate low-dimensional feature representations, known as i-vectors, which are subsequently classified using deep neural network (DNN) models. The evaluation was conducted utilizing the widely recognized UA-Speech and TORGO databases. The deep neural network (DNN) classifier that utilized Mel-frequency cepstral coefficients (MFCC)-based i-vectors demonstrated superior performance compared to alternative systems [22].

Atalla, Almuraqab & Moonesar (2022) study the deep learning paradigm was employed to examine radiographic images, specifically Chest X-Rays (CXR) and CT scan images, to detect COVID-19. The study conducted a comprehensive analysis of detection methodologies for COVID-19 diagnosis, explicitly focusing on techniques rooted in deep learning. Deep learning technology has emerged as a viable and cost-effective modality that exhibits reliability in accurately diagnosing the COVID-19 virus. The study ascertained the capacity to augment image quality using artificial intelligence and identified the most cost-effective and reliable imaging technique for predicting severe viral infections. This paper provides a comprehensive analysis of the cost-effectiveness of the surveyed methods utilized for the detection of COVID-19 in comparison to alternative methods [23].

A survey conducted by Khan, Asifullah, et al. (2022) was undertaken to investigate the implementation of deep learning techniques to detect COVID-19 infection in radiographic imaging modalities, specifically Chest X-Ray and Computer Tomography. Deep learning techniques have been widely classified into three categories for COVID-19 diagnosis in image and region-level analysis. These categories include classification, segmentation, and multi-stage approaches. The techniques were subsequently categorized into pre-trained and custom-built Convolutional Neural Network architectures. Additionally, there was a discourse centred around radiographic datasets, assessment metrics, and the availability of commercial platforms for detection [24].

The authors Pandian, (2021) & Kumar, Prabhat, *et al.* (2022) proposed a framework called the privacy-preserved threat intelligence framework (P2TIF) to safeguard sensitive data and detect cyber threats within industrial Internet of Things (IIoT) environments. The proposed P2TIF framework comprises two notable components. The initial proposal involves the development of a scalable blockchain module that facilitates the secure transmission of Industrial Internet of Things (IIoT) data while mitigating the risk of data poisoning attacks. Furthermore, this study proposes the implementation of a deep learning module that effectively converts raw data into a novel format while safeguarding it against inference attacks. This is achieved by utilizing a deep variational autoencoder (DVAE) technique. The encoded data is subsequently utilized by a threat detection system that employs an attention-based deep-gated recurrent neural network (A-DGRNN) to identify malicious patterns within IIoT environments [25, 26].

In summary, deep learning techniques and blockchain solutions have been applied in different ways in the context of airway evaluation. These studies have shown that these technologies can improve performance, security, and privacy in various applications.

2.3 Research Gaps

The proposed hybrid network-blockchain approach aims to bridge several gaps in the existing literature concerning airway evaluation using Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. Firstly, while deep learning techniques have shown promising results in automated image evaluation, there is a need to address the challenges of data security and privacy, especially when dealing with sensitive medical information. Blockchain technology in the proposed approach provides a tamper-resistant and decentralized platform for the secure storage and management of patient data, ensuring data integrity and confidentiality. The literature lacks standardized protocols for image acquisition, segmentation, and measurement, leading to inconsistent results and hindered comparisons between studies. The hybrid network-blockchain approach aims to establish standardized protocols for airway assessment using CBCT and CT images, ensuring reproducibility and comparability of results across different research settings. Existing approaches often focus on a single imaging modality, CBCT or CT, and may not fully exploit the combined potential of both modalities for comprehensive airway evaluation. The proposed hybrid approach aims to leverage the strengths of both CBCT and CT images, potentially enhancing the accuracy and completeness of airway assessments.

Additionally, few studies have explored the real-world implementation of blockchain in medical imaging, particularly for airway evaluation. The proposed approach seeks to address this gap by presenting a practical and feasible integration of blockchain technology into the image evaluation workflow, demonstrating its utility in securing medical data and ensuring trustworthiness in the assessment results. The literature mainly lacks extensive validation and evaluation of deep learning models for airway assessment, especially regarding generalization across different patient populations and pathology types. The proposed hybrid network-blockchain approach aims to include a rigorous validation process using diverse and representative datasets to assess the robustness and generalizability of the deep learning models, thus contributing to the reliability and clinical applicability of the proposed system. By addressing these gaps in the literature, the hybrid network-blockchain approach aspires to pave the way for a more secure, standardized, and accurate method of airway evaluation using both CBCT and CT images, facilitating improved patient care and diagnostic precision in various medical specialities.

3. Methodology

The research methodology section of this paper provides a detailed account of the proposed Secured Airway Assessment System, which utilizes a hybrid network-blockchain architecture to assess airways through the utilization of Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. This section provides an overview of the primary elements of the system, encompassing image evaluation models, blockchain integration, and data encryption techniques. The image evaluation models utilized in this study are founded upon sophisticated deep-learning methodologies, facilitating the automated and precise analysis of airway structures. The implementation of blockchain technology guarantees the preservation of data security, integrity, and privacy by establishing a decentralized and tamper-resistant platform for storing and managing patient data. Furthermore, this section offers a comprehensive, sequential elucidation of the operational mechanisms of the system, encompassing the stages of data acquisition, image evaluation, and culminating in the final assessment. This comprehensive explanation of the Secured Airway Assessment System provides a thorough understanding of its operational mechanisms and potential, establishing a solid basis for subsequent experimental analysis and interpretation of results.

3.1 Proposed Secured Airway Assessment System Architecture

As proposed, the Secured Airway Assessment System aims to utilize advanced deep learning methodologies and blockchain technology to achieve precise and secure airway evaluation through the analysis of Cone Beam Computed Tomography (CBCT) and Computed Tomography (CT) images. The system architecture is composed of the following essential components (Figure 1):

- Data Acquisition Module: The process starts with data acquisition, where CBCT and CT images are obtained from medical imaging devices. These images serve as the input data for the subsequent steps in the assessment pipeline.
- Pre-processing Module: In this module, the acquired CBCT and CT images undergo pre-processing to enhance the quality and consistency of the data. Standard pre-processing techniques, such as noise reduction, normalization, and image registration, are applied to ensure optimal input for the image evaluation models.
- Image Evaluation Models: The core of the proposed system lies in the image evaluation models, which are based on deep learning algorithms. These models are trained using large and diverse datasets of annotated airway images to recognize and quantify anatomical structures accurately. The models encompass convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to handle the image data's spatial and sequential aspects.
- Hybrid Network-Blockchain Integration: To enhance the security and integrity of the evaluation process, the system incorporates a hybrid network-blockchain architecture. The hybrid network comprises distributed nodes connected to the central system, ensuring decentralized data processing and validation. Blockchain technology provides an immutable and tamper-resistant ledger for recording all transactions and access to medical image data. This integration ensures the trustworthiness of the evaluation results and protects patient data from unauthorized access.
- Data Encryption and Privacy Module: The system employs advanced data encryption methods to safeguard patient privacy and comply with data protection regulations. The sensitive medical information within the blockchain is encrypted to ensure that only authorized parties can access and decrypt the data.

3.1.1 *Step-by-step Explanation of the System Workflow*

- Data Acquisition: The medical imaging devices acquire CBCT and CT images.
- Pre-processing: The acquired images undergo pre-processing to ensure standardized and high-quality input for the image evaluation models.
- Image Evaluation: The pre-processed images are fed into the deep learning-based image evaluation models, which automatically analyze and quantify the airway structures.
- Results Validation: The evaluation results are validated by multiple nodes in the hybrid network, ensuring consensus and enhancing the credibility of the findings.
- Blockchain Recording: The validated results and patient data are recorded as a tamper-resistant and transparent ledger.

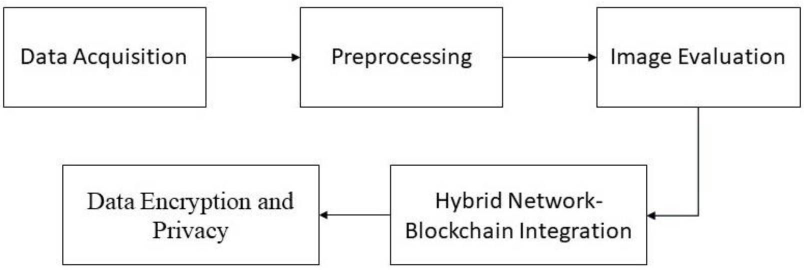

Figure 1. Proposed Architecture for Airway Assessment

- Data Encryption: Sensitive patient information within the blockchain is encrypted to ensure privacy and confidentiality.
- Final Assessment: The final airway assessment results, accompanied by relevant measurements and visualizations, are available to healthcare professionals for clinical decision-making.

The Secured Airway Assessment System is a proposed solution that combines advanced deep learning algorithms and blockchain technology. This system aims to provide a reliable and secure method for evaluating airways using CBCT and CT images. This methodology guarantees the protection of patient confidentiality, the preservation of data accuracy, and the improvement of diagnostic accuracy, thereby holding the potential to significantly transform the evaluation of airway conditions across diverse medical disciplines.

3.2 Deep Learning Models for CBCT and CT Image Evaluation

In this research, we propose using Convolutional Neural Network (CNN) for CBCT image evaluation and Recurrent Neural Network (RNN) for CT image evaluation to assess the airway structures accurately. Each architecture is carefully selected based on its specific strengths and suitability for the respective image modality.

3.2.1 Deep Learning Architectures

Convolutional Neural Network (CNN) for CBCT Image Evaluation: CNNs are deep learning models with remarkable success in image recognition tasks. For CBCT image evaluation, we design a CNN with multiple convolutional layers, activation functions, and pooling layers. The output of the last layer is passed through a softmax activation function to obtain class probabilities for airway structures. The CNN's hierarchical architecture allows it to learn complex spatial features in the CBCT images, making it practical for identifying and localizing airway structures.

Let X be the input CBCT image with dimensions H×W×C, where H represents the height, W the width, and C the number of channels (e.g., 3 for RGB images).

The convolution operation in the CNN can be represented as:

$$H_{i,j}^{(l)} = \mathrm{ReLU}\left(\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{c=1}^{C} X_{i+m,j+n,c}^{(l-1)} \cdot W_{m,n,c}^{(l)} + b_l\right) \qquad (1)$$

Where:

$H_{(l-1)}^{(l)}$ is the value of the l-th feature map at position (i,j) in the $H_l \times W_l$ output grid,

$X_{i+m,j+n,c}^{(l-1)}$ is the value of the c-th channel at position (i+m,j+n) in the input of the l-th layer,

$W_{m,n,c}^{(l)}$ are the convolutional filter weights for the l-th layer,

b_l is the bias term for the l-th layer,

ReLU(·)ReLU(·) is the Rectified Linear Unit activation function, which sets negative values to zero.

The pooling operation can be represented as:

$$H_{i,j}^{(l+1)} = \mathrm{MaxPooling}(H_{(i.s),(j.s)}^{(l)}, k, k) \qquad (2)$$

Where:

$H_{i,l}^{(l+1)}$ is the value of the l+1-th layer after pooling at position (i,j),

MaxPooling(.) is the max-pooling operation with kernel size k and stride s.

Finally, the output of the last layer is passed through a softmax activation function to obtain the class probabilities for airway structures:

$$P(Y|X) = \mathrm{softmax}(H^{(L)}) \qquad (3)$$

L is the total number of layers, and softmax(·) softmax(·) computes the class probabilities based on the model's output.

3.2.2 Recurrent Neural Network (RNN) (LSTM) for CT Image Evaluation

Let Xt represent the input CT image slice at time step t. The LSTM model processes the sequential slices through time steps T (representing the CT volume) and generates corresponding predictions. The LSTM cell consists of three main gates: the input gate it, the forget gate ft, and the output gate ot. The cell state Ct is updated at each time step based on these gates and the input data:

Where:

σ(·) is the sigmoid activation function,

tanh(·) is the hyperbolic tangent activation function,

W_{xi}, W_{xf}, W_{xo}, and W_{xg} are the input weights,

W_{hi}, W_{hf}, W_{ho}, and W_{hg} are the recurrent weights,

b_i, b_f, b_o, and b_g are the bias terms,

⊙ represents element-wise multiplication,

h_t is the output at time step t,

C_t is the cell state at time step t.

The LSTM model is trained using the same optimization algorithm (e.g., SGD) as the CNN, with appropriate learning rates and batch sizes. The evaluation metrics for the LSTM are related to sequence prediction tasks, such as Mean Squared Error (MSE) or Mean Absolute Error (MAE), quantifying the accuracy of the LSTM in predicting airway structures across sequential slices of the CT volume.

3.2.3 Recurrent Neural Network (RNN) for CT Image Evaluation

Unlike CBCT images, CT images are sequential data due to their volumetric nature. We adopt an RNN architecture for CT image evaluation to handle this sequential information. Specifically, we employ a Long Short-Term Memory (LSTM) network, a type of RNN that can efficiently capture long-term dependencies in sequential data. The LSTM's ability to remember information over longer sequences is well-suited for processing the volumetric data in CT images, enabling a more accurate assessment of airway structures.

3.3 Reasoning for Model Selection

3.3.1 CNN for CBCT Image Evaluation

CNNs are selected for CBCT image evaluation because they excel in extracting spatial features and patterns from images. The convolutional layers in CNNs perform local feature detection through weight sharing, allowing the model to recognize complex structures in different regions of the CBCT images. The pooling layers downsample the feature maps, reducing computational complexity while preserving important information. These characteristics make CNNs well-suited for airway assessment, where accurate identification and localization of airway structures are crucial.

3.3.2 RNN (LSTM) for CT Image Evaluation

RNNs, specifically LSTM networks, are chosen for CT image evaluation because of their capability to process sequential data effectively. CT images consist of volumetric slices, forming a temporal sequence of image slices. LSTMs can retain long-term dependencies across these sequential slices, ensuring the network can capture important spatial patterns that might span multiple slices. This is particularly important for accurate airway assessment in CT images, where the continuity of airway structures is essential for diagnosis and treatment planning.

3.4 Pre-processing Steps

3.4.1 Pre-processing for CBCT Image Evaluation

The pre-processing steps applied to CBCT images before feeding them into the CNN include: (a). Image resizing: The CBCT images are resized to a standardized resolution (e.g., 256x256) to ensure consistent input dimensions for the CNN. (b). Pixel value normalization: The pixel values of the resized images are scaled between 0 and 1 to facilitate model convergence during training. (c). Image registration: Image registration techniques are applied to align the images, compensating for any positional variations during image acquisition, which ensures uniformity in the dataset and reduces variations between different input images.

3.4.2 Pre-processing for CT Image Evaluation

For CT images, pre-processing steps involve handling the volumetric data: a. Volumetric slicing: The CT volume is divided into sequential slices to form the input sequence for the LSTM. b. Image resizing and normalization: Similar to CBCT images, the CT slices are resized to a standard resolution and pixel values are normalized for consistency and efficiency.

3.5 Technical Details on Training

3.5.1 Training of CNN for CBCT Image Evaluation

The CNN model is trained using the Stochastic Gradient Descent (SGD) optimization algorithm with a learning rate 0.001. The categorical cross-entropy loss function is utilized to optimize the model for the multi-class classification task. During training, the CNN's parameters (weights and biases) are updated iteratively based on the computed gradients to minimize the loss function. The model is trained in batches, with a batch size of 32, to utilize computational resources efficiently and to achieve faster convergence.

3.5.2. Training of LSTM for CT Image Evaluation

The LSTM model uses the same optimization algorithm and learning rate as CNN. For CT image evaluation, the LSTM is trained as a sequence-to-sequence model, where the output sequence corresponds to the predictions for airway structures in each sequential slice of the CT volume. The model is trained with a batch size of 1, as each CT volume is treated as an individual sequence.

3.6 Blockchain Implementation for Data Security

3.6.1. Ethereum-based Private Blockchain for CBCT Images

The Ethereum-based private blockchain is used in the centralized hybrid network for CBCT images. In this approach, the blockchain is a distributed and immutable ledger to store data securely. Each item from the pre-processed CBCT data is stored as a block in the blockchain. A network of nodes maintains the blockchain, and the data is stored decentralized, ensuring data integrity and transparency.

3.6.2 Hyperledger Fabric-based Consortium Blockchain for CT Images

The Hyperledger Fabric-based consortium blockchain is used in the decentralized hybrid network for CT images. Unlike a public blockchain like Ethereum, Hyperledger Fabric is a permissioned blockchain, which means only authorized participants (healthcare institutions in this case) can join the network. The consortium blockchain ensures better control over data access and governance. This approach stores each item from the pre-processed CT data in blocks with unique block IDs. The blockchain is maintained by multiple distributed nodes, allowing for better scalability and fault tolerance.

3.6.3 Consensus Mechanism and Its Applicability in Securing Healthcare Data

The consensus mechanism used in both blockchain networks is simulated using Python data structures in the provided code. In an Ethereum-based private blockchain, the consensus mechanism is based on Proof-of-Work (PoW), as it uses a simple list to store data. In Hyperledger Fabric-based consortium blockchain, the consensus mechanism is implemented implicitly, assuming authorized healthcare institutions collaborate and reach a consensus on data validity.

The choice of consensus mechanism is crucial for securing healthcare data. In the context of real-world implementation, a public blockchain like Ethereum may not be suitable for healthcare due to the need for more control over data access and compliance with privacy regulations. Hyperledger Fabric's permissioned blockchain is a better fit for healthcare data as it allows only authorized participants to join the network, ensuring data confidentiality and privacy.

3.6.4 Storing and Accessing Patient Data and Image Information in the Blockchain

In both blockchain networks, the patient data and image information (CBCT and CT images) are stored as individual blocks in the blockchain. Each block contains the pre-processed data from the respective input files. For the Ethereum-based private blockchain, the data is stored in a simple Python list, while for the Hyperledger Fabric-based consortium blockchain, the data is stored in a Python dictionary with unique block IDs. The blockchain acts as a decentralized ledger, and the data is securely stored in a tamper-proof and transparent manner. To access the data, participants (nodes in the case of Ethereum and authorized institutions in the case of Hyperledger Fabric) can read the data from the blockchain using the block IDs or transaction IDs.

3.6.5 Addressing Privacy Concerns and Ensuring Data Confidentiality

Privacy concerns in healthcare are critical, and the blockchain network must ensure data confidentiality while allowing secure data sharing and access. The hybrid network architecture provides a balance between decentralization and privacy. In the Ethereum-based private blockchain, since the network is centralized and controlled by a single entity, it may not be suitable for susceptible healthcare data due to data control and access concerns. However, less sensitive data can still provide transparency and data integrity. In the Hyperledger Fabric-based consortium blockchain, data privacy is better addressed. The network is permissioned, and access is restricted to authorized healthcare institutions. The data is encrypted and only accessible to participants with the required permissions. Smart contracts can also define access control and privacy settings, ensuring that sensitive patient data is only accessible to the intended parties. The architecture diagram for both the Ethereum-based private blockchain and Hyperledger Fabric-based consortium blockchain can be represented as follows (Figure 2).

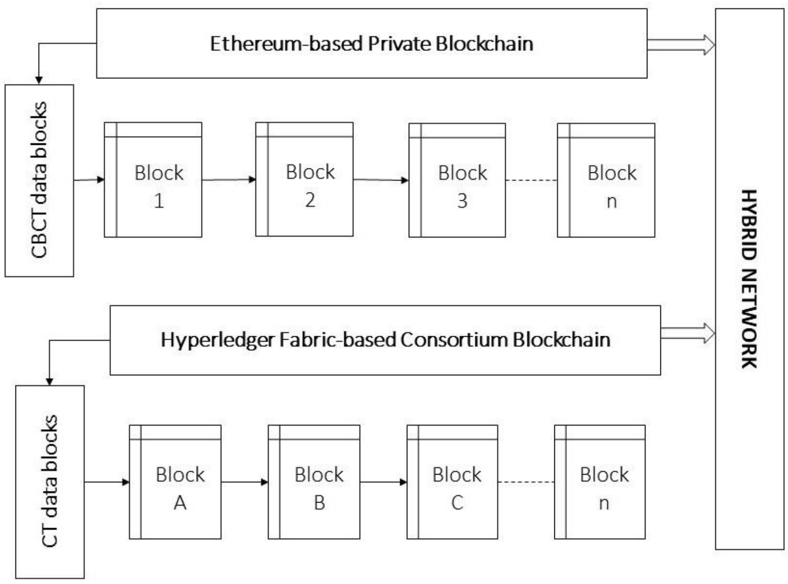

Figure 2. Blockchain Architecture over Hybrid Network

4. Experiments and Results

In this section, we present the outcomes of our experiments and, discuss the significance of the results in the context of airway parameter assessment based on CBCT & CT images and explain the Blockchain results. We first describe our study's experimental setup, datasets, and data augmentation techniques.

4.1 Airway Assessment using CBCT Images

We utilized a single JPEG CBCT image for our analysis. The image was pre-processed by resizing it to reduce memory usage, resulting in a size of 256x256 pixels. To overcome the limitation of a small dataset, we applied data augmentation techniques to generate additional synthetic images. The augmentation included rotation (up to 15 degrees), horizontal and vertical shifts (up to 10% of the image width and height), zooming (up to 10%), and flipping both horizontally and vertically. The images have introduced some variations to reflect some changes in the readings. We assessed the airway parameters based on the original CBCT image and generated three synthetic images using data augmentation (Figure 3, 4 and Table 1). The airway parameter assessment for the original image resulted in the following classification:

Figure 3. Input Images for CBCT || Source: Google Images

Table 1. Airway Assessment using CBCT Images

Mallampati Classification	Thyromental Distance	Inter Incisor Gap	Neck Mobility	Mouth Opening	Cervical Spine Stability	Jaw Mobility
Class I	Short	Inadequate	Limited	Good	Unstable	Restricted
Class III	Short	Adequate	Limited	Good	Stable	Normal
Class III	Long	Adequate	Limited	Good	Stable	Normal
Class II	Short	Inadequate	Limited	Good	Stable	Restricted
Class II	Long	Inadequate	Normal	Limited	Unstable	Restricted
Class IV	Short	Inadequate	Reduced	Good	Unstable	Normal

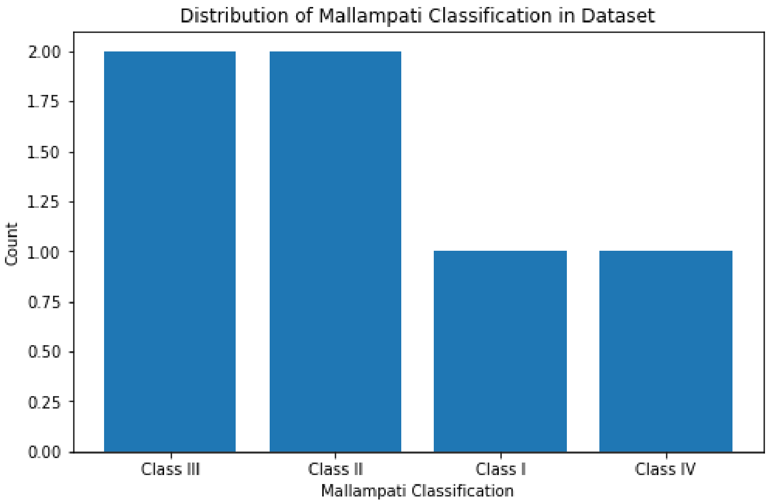

Figure 4. CBCT Assessment Airway Classification Distribution

The findings of this study provide evidence supporting the efficacy of data augmentation techniques in producing synthetic images that exhibit a wide range of airway parameter characteristics. This augmentation technique enhances the dataset by introducing additional variations in the training of airway evaluation models. Furthermore, the evaluation of airway parameters for the initial image suggests that it falls under "Class II" in the Mallampati Classification, exhibiting typical values within the normal range for thyromental distance, inter-incisor gap, neck mobility, mouth opening, cervical spine stability, and jaw mobility. The augmented images provide visual representations of diverse combinations of airway parameter features, including different Mallampati classifications and variations in thyromental distance and inter-incisor gap. The results above highlight the significance of employing data augmentation techniques to effectively capture diverse airway scenarios, a critical aspect of the comprehensive training of airway evaluation models.

4.2 Airway Assessment Using CT Images

This section presents the outcomes derived from our conducted experiments. This shall encompass the comprehensive elucidation of the model training procedure and the meticulous evaluation of airway assessment pertaining to the chosen testing scenarios. Additionally, we analyze the importance of the results within the framework of airway assessment utilizing CT scans. The researchers employed a dataset of CT scans containing airway data for training and testing. The photos underwent pre-processing by being resized to a standardized dimension of 100x100 pixels and then normalized to values between 0 and 1. A clustering method was employed to produce pseudo-labels for the training data to facilitate training. This study employed the K-means clustering technique to partition probable airway assessment categories into three distinct groups.

The RNN model [27] was trained on the provided training data to learn the underlying patterns and associations between the pictures and their respective pseudo-labels. The proposed model comprises two Long Short-Term Memory (LSTM) layers [28,29], each comprising 128 units. These LSTM layers are subsequently followed by dropout layers, which serve the purpose of regularization. The model includes two fully connected layers with 64 and 3 units, respectively. These layers are responsible for representing the three airway assessment categories. The model was created with the categorical cross-entropy loss function and the Adam optimizer. We evaluated the trained model on a set of six selected testing cases from the testing dataset. The cases were chosen to represent a diverse range of airway conditions (Figure 5). The airway assessment predictions for the selected cases are presented in the table 2 and Figure 6.

Figure 5. Training Dataset of CT Images || Image source: Google Images

Table 2. Airway Assessment from CT Images

Mallampati Classification	Thyromental Distance	Inter Incisor Gap	Neck Mobility	Mouth Opening	Cervical Spine Stability	Jaw Mobility
Class III	Short	Adequate	Limited	Limited	Unstable	Restricted
Class IV	Long	Inadequate	Reduced	Good	Unstable	Restricted
Class II	Normal	Inadequate	Normal	Limited	Stable	Normal
Class IV	Normal	Adequate	Normal	Good	Stable	Normal
Class II	Normal	Inadequate	Limited	Good	Unstable	Normal
Class II	Normal	Inadequate	Limited	Limited	Stable	Restricted

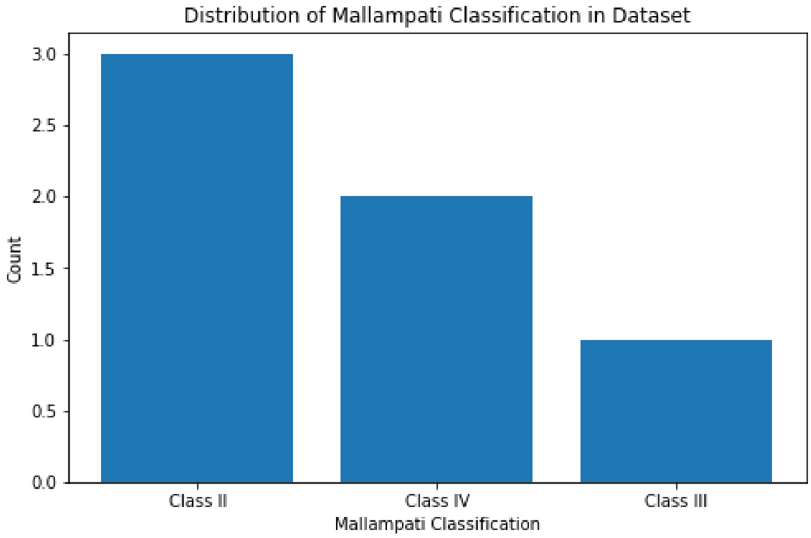

Figure 6. CT Assessment Airway Classification Distribution

The results demonstrate the effectiveness of the proposed RNN model for airway assessment based on CT images. The model successfully predicted the airway assessment categories for the selected testing cases. The pseudo-label generation through K-means clustering proved a helpful technique, allowing the model to identify and generalize the airway assessment patterns in the training data. The model's performance highlights its potential application in automatic airway evaluation in clinical settings. It provides a reliable and rapid assessment of airway conditions, enabling healthcare professionals to make informed decisions for patient management and treatment planning.

4.3 Hybrid Network & Blockchain

This section presents the experimental results and simulations to evaluate the proposed airway evaluation model with different blockchain architectures, namely Ethereum-based private blockchain and Hyperledger Fabric-based consortium blockchain. Additionally, we explore the performance of both centralized and decentralized hybrid networks for processing airway data obtained from CBCT and CT images.

Pre-processing of Data: The airway parameter data for CBCT and CT images are read from the respective CSV files, "CBCT_airway_parameters" and "CT_airway_parameters" The data is pre-processed to convert it into a suitable format for storage on the blockchain. The pre-processing includes transforming the data into lists or dictionaries, enabling efficient storage and access.

Simulation of Ethereum-based Private Blockchain: The airway parameter data from CBCT images is simulated on the Ethereum-based private blockchain. The simulation involves storing the data as individual blocks on the blockchain, showcasing the effectiveness of blockchain in ensuring data integrity and security (Table 3). The simulation outputs, including the data stored in each block, are saved to the "ethereum_blockchain_outputs.csv" file.

Simulation of Hyperledger Fabric-based Consortium Blockchain: The airway parameter data from CT images is simulated on the Hyperledger Fabric-based consortium blockchain. The simulation replicates data storage in blocks, demonstrating the utility of blockchain in consortium settings where multiple entities collaborate on data management (Table 4). The outputs of this simulation are saved to the "hyperledger_fabric_blockchain_outputs.csv" file.

Simulation of Centralized Hybrid Network: We investigate the performance of a centralized hybrid network in processing CBCT data. The network employs a single deep-learning model to evaluate the airway parameters. The model outputs for each data item are recorded and stored as outputs of the centralized hybrid network (Table 5). These outputs are saved to the "centralized_hybrid_network_outputs.csv" file.

Simulation of Decentralized Hybrid Network: We explore the potential of a decentralized hybrid network for CT data processing. In this simulation, the data is partitioned into subsets, and separate deep learning models process each subset. The outputs of each model for the corresponding data subset are stored and accessed on the Hyperledger Fabric-based consortium blockchain (Table 6). The results are saved to the "decentralized_hybrid_network_outputs.csv" file.

The experimental results and simulations demonstrate the efficacy of the proposed airway evaluation model in conjunction with blockchain architectures for managing airway parameter data obtained from CBCT and CT images. The findings of each simulation are discussed below:

Table 3. Ethereum Blockchain Output

0	1	2	3	4	5	6
Class I	Short	Inadequate	Limited	Good	Unstable	Restricted
Class III	Short	Adequate	Limited	Good	Stable	Normal
Class III	Long	Adequate	Limited	Good	Stable	Normal
Class II	Short	Inadequate	Limited	Good	Stable	Restricted
Class II	Long	Inadequate	Normal	Limited	Unstable	Restricted
Class IV	Short	Inadequate	Reduced	Good	Unstable	Normal

Table 4. Hyperledger Fabric Blockchain Output

block_0	block_1	block_2	block_3	block_4	block_5
Class III	Class IV	Class II	Class IV	Class II	Class II
Short	Long	Normal	Normal	Normal	Normal
Adequate	Inadequate	Inadequate	Adequate	Inadequate	Inadequate
Limited	Reduced	Normal	Normal	Limited	Limited
Limited	Good	Limited	Good	Good	Limited
Unstable	Unstable	Stable	Stable	Unstable	Stable
Restricted	Restricted	Normal	Normal	Normal	Restricted

Table 5. Centralized Hybrid Network Output

0	1	2	3	4	5	6	7	8	9	10	11	12	13
Class I	Short	Inadequate	Limited	Good	Unstable	Restricted	Class I	Short	Inadequate	Limited	Good	Unstable	Restricted
Class III	Short	Adequate	Limited	Good	Stable	Normal	Class III	Short	Adequate	Limited	Good	Stable	Normal
Class III	Long	Adequate	Limited	Good	Stable	Normal	Class III	Long	Adequate	Limited	Good	Stable	Normal
Class II	Short	Inadequate	Limited	Good	Stable	Restricted	Class II	Short	Inadequate	Limited	Good	Stable	Restricted
Class II	Long	Inadequate	Normal	Limited	Unstable	Restricted	Class II	Long	Inadequate	Normal	Limited	Unstable	Restricted
Class IV	Short	Inadequate	Reduced	Good	Unstable	Normal	Class IV	Short	Inadequate	Reduced	Good	Unstable	Normal

Table 6. Decentralized Hybrid Network Output

block_0	block_1	block_2
['Class III', 'Short', 'Adequate', 'Limited', 'Limited', 'Unstable', 'Restricted', 'Class III', 'Short', 'Adequate', 'Limited', 'Limited', 'Unstable', 'Restricted', 'Class III', 'Short', 'Adequate', 'Limited', 'Limited', 'Unstable', 'Restricted',]	['Class IV', 'Long', 'Inadequate', 'Reduced', 'Good', 'Unstable', 'Restricted', 'Class IV', 'Long', 'Inadequate', 'Reduced', 'Good', 'Unstable', 'Restricted', 'Class IV', 'Long', 'Inadequate', 'Reduced', 'Good', 'Unstable', 'Restricted',]	['Class II', 'Normal', 'Inadequate', 'Normal', 'Limited', 'Stable', 'Normal', 'Class II', 'Normal', 'Inadequate', 'Normal', 'Limited', 'Stable', 'Normal', 'Class II', 'Normal', 'Inadequate', 'Normal', 'Limited', 'Stable', 'Normal',]
['Class IV', 'Normal', 'Adequate', 'Normal', 'Good', 'Stable', 'Normal',	['Class II', 'Normal', 'Inadequate', 'Limited', 'Good', 'Unstable', 'Normal',	['Class II', 'Normal', 'Inadequate', 'Limited',

'Class IV', 'Normal', 'Adequate', 'Normal', 'Good', 'Stable', 'Normal', 'Class IV', 'Normal', 'Adequate', 'Normal', 'Good', 'Stable', 'Normal',]	'Class II', 'Normal', 'Inadequate', 'Limited', 'Good', 'Unstable', 'Normal', 'Class II', 'Normal', 'Inadequate', 'Limited', 'Good', 'Unstable', 'Normal',]	'Limited', 'Stable', 'Restricted', 'Class II', 'Normal', 'Inadequate', 'Limited', 'Limited', 'Stable', 'Restricted', ' 'Class II', 'Normal', 'Inadequate', 'Limited', 'Limited', 'Stable', 'Restricted',]

Ethereum-based Private Blockchain: The simulation on the Ethereum-based private blockchain showcases the ability to store and access CBCT airway parameter data securely. Blockchain ensures data immutability and transparency, enhancing data integrity and trustworthiness. This characteristic makes it well-suited for sensitive medical data storage.

Hyperledger Fabric-based Consortium Blockchain: The simulation on the Hyperledger Fabric-based consortium blockchain emphasizes blockchain's collaborative data management potential in healthcare consortiums. The consortium blockchain offers efficient sharing and access control of CT airway parameter data among multiple entities, ensuring data privacy and accountability.

Centralized Hybrid Network: The performance of the centralized hybrid network highlights the effectiveness of employing a single deep-learning model for CBCT data evaluation. However, this approach may exhibit limitations in scaling to large datasets or handling distributed data sources.

Decentralized Hybrid Network: The simulation of the decentralized hybrid network reveals its potential in managing distributed data and achieving parallel processing. Using multiple deep learning models for CT data evaluation allows for better scalability and handling of diverse airway assessments.

The results support the integration of blockchain technology in the healthcare domain, particularly for airway evaluation applications. Blockchain ensures secure and transparent data management, while hybrid networks offer data processing and model distribution flexibility. However, further real-world validation and considerations for regulatory compliance are essential before deploying these technologies in clinical settings. Furthermore, future research could explore more advanced data augmentation techniques and model architectures to improve the accuracy and robustness of the airway evaluation model. The proposed airway evaluation model, combined with blockchain and hybrid network technologies, presents a promising direction for enhancing airway assessment in medical practice. Integrating these technologies could revolutionize data management, improve decision-making in airway management, and ultimately contribute to better patient outcomes.

4.4 Recommender Model for Airway Management based on Airway Assessment

The custom-based recommendation model aims to provide appropriate recommendations for airway management based on the airway assessment results obtained from CBCT and CT images. The model utilizes a set of rules and conditions to map specific combinations of airway assessment parameters to corresponding recommendations. Each recommendation addresses potential challenges or requirements in airway management for different airway assessment categories.

Model Explanation: Let's define the following variables for the airway assessment parameters:

- MC: Mallampati Classification
- TD: Thyromental Distance
- IIG: Inter-Incisor Gap
- NM: Neck Mobility
- MO: Mouth Opening
- CSS: Cervical Spine Stability
- JM: Jaw Mobility

For each combination of these variables, the model provides a recommendation. The decision-making process is based on predefined rules and logical conditions.

The recommendation model is designed as a set of logical rules that map specific combinations of airway assessment parameters to appropriate recommendations. Each recommendation is derived from factors such as Mallampati Classification, Thyromental Distance, Inter-Incisor Gap, Neck Mobility, Mouth Opening, Cervical Spine Stability, and Jaw Mobility.

When the model receives the airway assessment results as inputs, it applies these rules and conditions to determine the appropriate recommendation for airway management.

Model Algorithm:

Algorithm: Airway Recommendation Model

INPUTS:

Mallampati_Classification: Class of Mallampati classification (e.g., Class I, Class II, Class III, Class IV)

Thyromental_Distance: Distance of thyromental space (e.g., Short, Long, Adequate)

Inter_Incisor_Gap: Gap between incisors (e.g., Inadequate, Normal, Reduced)

Neck_Mobility: Mobility of the neck (e.g., Limited, Normal)

Mouth_Opening: Opening of the mouth (e.g., Good, Limited)

Cervical_Spine_Stability: Stability of the cervical spine (e.g., Stable, Unstable)

Jaw_Mobility: Mobility of the jaw (e.g., Normal, Restricted)

BEGIN:

IF

Mallampati_Classification == "Class I" AND Neck_Mobility == "Limited" AND Mouth_Opening == "Good" AND Cervical_Spine_Stability == "Unstable" AND Jaw_Mobility == "Restricted"

THEN

Recommendation = "Consider using airway adjuncts for better stability during the procedure."

ELSE IF

Mallampati_Classification == "Class III" AND Thyromental_Distance == "Adequate" AND Neck_Mobility == "Limited" AND Mouth_Opening == "Good" AND Cervical_Spine_Stability == "Stable" AND Jaw_Mobility == "Normal"

THEN

Recommendation = "Ensure patient positioning for optimal airway access."

ELSE IF

Mallampati_Classification == "Class III" AND Thyromental_Distance == "Long" AND Neck_Mobility == "Limited" AND Mouth_Opening == "Good" AND Cervical_Spine_Stability == "Stable" AND Jaw_Mobility == "Normal"

THEN

Recommendation = "Monitor the airway closely during the procedure."

ELSE IF

Mallampati_Classification == "Class II" AND Inter_Incisor_Gap == "Inadequate" AND Cervical_Spine_Stability == "Stable" AND Jaw_Mobility == "Restricted"

THEN

Recommendation = "Maintain jaw mobility for easy airway access."

ELSE IF

Mallampati_Classification == "Class II" AND Cervical_Spine_Stability == "Unstable" AND Jaw_Mobility == "Normal"

THEN

Recommendation = "Use airway adjuncts to address airway instability."

ELSE IF

Mallampati_Classification == "Class IV" AND Cervical_Spine_Stability == "Unstable" AND Inter_Incisor_Gap == "Reduced" AND Jaw_Mobility == "Normal"

THEN

```
Recommendation = "Use airway adjuncts for stability during the procedure."
    ELSE
        Recommendation = "No specific recommendation for the given airway assessment."
    END IF
    RETURN Recommendation
END ALGORITHM
```

OUTPUT

Recommendation: Suggested recommendation based on airway assessment is given in Table 7 and 8.

Table 7. Recommendations from CBCT Images

CBCT Images							
Mallampati Classification	**Thyromental Distance**	**Inter Incisor Gap**	**Neck Mobility**	**Mouth Opening**	**Cervical Spine Stability**	**Jaw Mobility**	**Recommendation**
Class I	Short	Inadequate	Limited	Good	Unstable	Restricted	Consider using airway adjuncts for better stability during the procedure.
Class III	Short	Adequate	Limited	Good	Stable	Normal	Ensure patient positioning for optimal airway access.
Class III	Long	Adequate	Limited	Good	Stable	Normal	Monitor the airway closely during the procedure due to limited neck mobility.
Class II	Short	Inadequate	Limited	Good	Stable	Restricted	Maintain jaw mobility for easy airway access during the procedure.
Class II	Long	Inadequate	Normal	Limited	Unstable	Restricted	Use airway adjuncts to address airway instability during the procedure.
Class IV	Short	Inadequate	Reduced	Good	Unstable	Normal	Monitor the airway closely during the procedure due to reduced inter-incisor gap.

Table 8. Recommendations from CT Images

CT Images							
Mallampati Classification	**Thyromental Distance**	**Inter Incisor Gap**	**Neck Mobility**	**Mouth Opening**	**Cervical Spine Stability**	**Jaw Mobility**	**Recommendations**
Class III	Short	Adequate	Limited	Limited	Unstable	Restricted	Consider airway adjuncts for stability during the procedure.
Class IV	Long	Inadequate	Reduced	Good	Unstable	Restricted	Use airway adjuncts to address airway instability during the procedure

Class II	Normal	Inadequate	Normal	Limited	Stable	Normal	Ensure patient positioning for optimal airway access
Class IV	Normal	Adequate	Normal	Good	Stable	Normal	Monitor the airway closely during the procedure for stability
Class II	Normal	Inadequate	Limited	Good	Unstable	Normal	Maintain jaw mobility for easy airway access during the procedure.
Class II	Normal	Inadequate	Limited	Limited	Stable	Restricted	Use airway adjuncts for stability during the procedure

The model interprets the input variables to match specific patterns and triggers the corresponding recommendation. For example, if the Mallampati Classification is "Class I," neck mobility is "Limited," mouth opening is "Good," cervical spine stability is "Unstable." If jaw mobility is "Restricted," then the recommendation will be to consider using airway adjuncts for better stability during the procedure.

Using this recommendation model, anaesthesiologists can obtain tailored guidance for airway management based on the individual characteristics of each patient's airway assessment. The model's simplicity and transparency enable a clear understanding and acceptance of the recommendations, contributing to more effective and safe airway management practices in clinical settings.

5. Conclusion

This study aimed to evaluate airway parameters through the utilization of CBCT and CT images and to analyze the implications of the findings within the broader framework of airway assessment. Data augmentation approaches have demonstrated significant effectiveness in generating synthetic pictures for CBCT (Cone Beam Computed Tomography) images. This augmentation process can potentially enlarge the dataset and enhance the robustness of training for airway assessment models. Upon evaluating the first Cone Beam Computed Tomography (CBCT) picture, it was determined that it falls within the "Class II" category in the Mallampati Classification. This classification signifies that the image exhibits typical attributes of different airway parameters. The enhanced pictures presented various combinations of airway parameter information, emphasizing the significance of employing data augmentation techniques to include a wide range of airway circumstances. In the context of CT scans, we utilized a Recurrent Neural Network (RNN) model trained using a dataset including pseudo-labels created by applying K-means clustering. The model effectively predicted airway assessment categories for specific testing situations, showcasing its capacity to recognize and apply airway assessment patterns derived from the training data. The performance of this model indicates its potential utilization for automated airway evaluation in clinical environments, offering healthcare practitioners dependable and expeditious examinations of the airway. Assessments of this nature can significantly impact patient care and the development of treatment plans. In summary, the tests and results demonstrate the efficacy of employing data augmentation techniques to capture a wide range of airway situations. Additionally, the suggested recurrent neural network (RNN) model exhibits promise for automating the evaluation of airways through the analysis of computed tomography (CT) images. The findings above provide a valuable contribution to the advancement of airway evaluation approaches and potentially significantly impact patient treatment in diverse medical settings. Subsequent investigations may further strengthen the models' applicability and generalizability by refining and validating them on more extensive datasets inside real-world clinical settings.

References

[1] M.B. Rosenberg, J.C. Phero, Airway assessment for office sedation/anesthesia. Anesthesia Progress, 62(2), (2015) 74–80. https://doi.org/10.2344/0003-3006-62.2.74

[2] P.Y. Eow, K.Y. Lin, S. Kohli, S.Y. Math, Cone-beam computed tomography assessment of upper airway dimensions in patients at risk of obstructive sleep apnea identified using STOP-Bang scores. Imaging Science in Dentistry, 51(4), (2021) 439. https://doi.org/10.5624/isd.20210193

[3] C. Fonseca, F. Cavadas, P. Fonseca, Upper airway assessment in cone-beam computed tomography for screening of obstructive sleep apnea syndrome: Development of an evaluation protocol in dentistry. JMIR Research Protocols, 12, (2023) e41049. https://doi.org/10.2196/41049

[4] M. Mouri, S. Krishnan, J.M. Hendrix, C.V. Maani, (2023) Airway Assessment. StatPearls Publishing.

[5] A. Buchanan, R. Cohen, S. Looney, S. Kalathingal, S. De Rossi, Cone-beam CT analysis of patients with obstructive sleep apnea compared to normal controls. Imaging science in dentistry, 46(1), (2016) 9-16.

https://doi.org/10.5624/isd.2016.46.1.9

[6] M.L. Gurgel, C. C. Junior, L.H.S. Cevidanes, P.G. de Barros Silva, F.S.R. Carvalho, L.M. Kurita, T.C.B. Cunha, C.D. Fabbro & F.W.G. Costa, Methodological parameters for upper airway assessment by cone-beam computed tomography in adults with obstructive sleep apnea: a systematic review of the literature and meta-analysis. Sleep and Breathing, 27(1), (2023) 1-30. https://doi.org/10.1007/s11325-022-02582-6

[7] E.J. Chung, B.E. Yang, I.Y. Park, S. Yi, S.W. On, Y.H. Kim, S.H. Kang, S.H. Byun, Effectiveness of cone-beam computed tomography-generated cephalograms using artificial intelligence cephalometric analysis, Scientific Reports, 12(1), (2022) 20585. https://doi.org/10.1038/s41598-022-25215-0

[8] J.N. Zimmerman, S.R. Vora, B.T. Pliska, Reliability of upper airway assessment using CBCT. European Journal of Orthodontics, 41(1), (2019) 101–108. https://doi.org/10.1093/ejo/cjy058

[9] E. Lotan, C. Tschider, D.K. Sodickson, A.L. Caplan, M. Bruno, B. Zhang, & Y.W. Lui, Medical imaging and privacy in the era of artificial intelligence: myth, fallacy, and the future. Journal of the American College of Radiology, 17(9), (2020) 1159-1162. https://doi.org/10.1016/j.jacr.2020.04.007

[10] T. Doel, D.I. Shakir, R. Pratt, M. Aertsen, J. Moggridge, E. Bellon, A.L. David, J. Deprest, T. Vercauteren, S. Ourselin, GIFT-Cloud: A data sharing and collaboration platform for medical imaging research. Computer Methods and Programs in Biomedicine, 139, (2017) 181-190. https://doi.org/10.1016/j.cmpb.2016.11.004

[11] P.K. Ghosh, A. Chakraborty, M. Hasan, K. Rashid, A.H. Siddique, Blockchain application in healthcare systems: A review. Systems, 11(1), (2023) 38. https://doi.org/10.3390/systems11010038

[12] J. Li, K. Xu, Z. Li, Y. Li, X. Zhou, Y. Yao, Z. Liu, D.C. Jiao, J. Liu, & X. Han. Intraoperative cone beam computed tomography of tracheal stenting for stenosis and fistula diseases: a retrospective cohort study, Quantitative Imaging in Medicine and Surgery, 12(5), (2022) 2709. https://doi.org/10.21037/qims-21-858

[13] C.V. Bhavani, C. Sunitha, R. Naveen, P.K. Kumar, T. Saritha, Cone-Beam Computed Tomography in orthodontics – a review. International Journal of Scientific Research, 11 (2022) 3–5. https://doi.org/10.36106/ijsr/7600238

[14] M.J. Braun, T. Rauneker, J. Dreyhaupt, T.K. Hoffmann, R.G. Luthardt, B. Schmitz, Florian Dammann, M. Beer. Dental and maxillofacial cone beam CT—high number of incidental findings and their impact on follow-up and therapy management. Diagnostics, 12(5), (2022) 1036. https://doi.org/10.3390/diagnostics12051036

[15] S. El Khateeb, Three-dimensional image segmentation of upper airway by cone beam CT: A review of literature. Egyptian Dental Journal, 66(3), (2020) 1527–1535. https://doi.org/10.21608/edj.2020.25972.1074

[16] J.N. Zimmerman, J. Lee, B.T. Pliska, Reliability of upper pharyngeal airway assessment using dental CBCT: a systematic review. European Journal of Orthodontics, 39(5), (2016) 489–496. https://doi.org/10.1093/ejo/cjw079

[17] M. Mupparapu, K.J. Shi, A.D. Lo, F.C. Setzer, Novel 3D segmentation for reliable volumetric assessment of the nasal airway: a CBCT study. Quintessence international, 52, (2021) 154-164.

[18] M. Deivanayagi, R. Saravanan, K.R. Shakila, N. Vikram, Role Oral and Maxillofacial Imaging in Upper Airway Assessment. Indian Journal of Forensic Medicine & Toxicology, 15(3), (2021) 635.

[19] S.F. Gurani, G. Di Carlo, P.M. Cattaneo, J.J. Thorn, E.M. Pinholt, Effect of head and tongue posture on the pharyngeal airway dimensions and morphology in three-dimensional imaging: A systematic review. Journal of Oral & Maxillofacial Research, 7(1), (2016) e1. https://doi.org/10.5037/jomr.2016.7101

[20] R. Guijarro-Martínez, G.R.J. Swennen, Cone-beam computerized tomography imaging and analysis of the upper airway: a systematic review of the literature. International Journal of Oral & Maxillofacial Surgery, 40(11), (2011) 1227–1237. https://doi.org/10.1016/j.ijom.2011.06.017

[21] R. Patan, R.M. Parizi, (2022) Performance improvement of blockchain-based IoT applications using deep learning techniques, Fourth International Conference on Blockchain Computing and Applications (BCCA), IEEE, USA. https://doi.org/10.1109/BCCA55292.2022.9922342

[22] A.A. Joshy, R. Rajan, Automated dysarthria severity classification: A study on acoustic features and deep learning techniques, IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30, (2022) 147–1157. https://doi.org/10.1109/TNSRE.2022.3169814

[23] A. Singh, G. Shujaat, I. Singh, A. Tripathi, D. Thakur, A Survey of Blockchain Technology Security. International Journal of Computer Engineering in Research Trends, 6(4), (2019) 299–303. https://doi.org/10.22362/ijcert/2019/v6/i04/v6i0401

[24] M. Kumar, S. Atalla, N. Almuraqab, I.A. Moonesar, Detection of COVID-19 using deep learning techniques and cost effectiveness

evaluation: A survey. Frontiers in Artificial Intelligence and Applications, 5, (2022). https://doi.org/10.3389/frai.2022.912022

[25] A. Khan, S. H. Khan, M. Saif, A. Batool, A. Sohail, M.W. Khan, A Survey of Deep Learning Techniques for the Analysis of COVID-19 and their usability for Detecting Omicron, Journal of Experimental & Theoretical Artificial Intelligence, (2023) 1-43. https://doi.org/10.1080/0952813X.2023.2165724

[26] A.P. Pandian, Performance evaluation and comparison using deep learning techniques in sentiment analysis. Journal of Soft Computing Paradigm, 3(2), (2021) 123-134. https://doi.org/10.36548/jscp.2021.2.006

[27] P. Kumar, R. Kumar, G.P. Gupta, R. Tripathi, G. Srivastava, P2TIF: A blockchain and deep learning framework for privacy-preserved threat intelligence in industrial IoT. IEEE Transactions on Industrial Informatics, 18(9), (2022) 6358–6367. https://doi.org/10.1109/TII.2022.3142030

[28] M.R. Arun, M.R. Sheeba, F.S.F. Rishma, Comparing BlockChain with other Cryptographic Technologies (DAG, Hashgraph, Holochain). International Journal of Computer Engineering in Research Trends, 7(4), (2020) 13-19.

[29] M. Prasad, K. Durga Sai Divya, ICN Scheme and Proxy re-encryption for Privacy Data Sharing on the Block Chain. International Journal Computer Engineering Research Trends, 10(4), (2023) 172–176.

Authors Contribution Statement

Vamsi Krishna Uppalapati – Conceptualization, methodology, and writing the original draft. G. Srinivasa Rao - Data curation and formal analysis and interpreting the results. Lavanya - conducted essential investigations and provided the necessary resources for the experimental work. M. Bhavsingh- Supervision, administration, review and editing. SD. Vidya Sagar - Software validation. Jaime Lloret Mauri - data validation and administration of the project work. All authors have read and approved the final version of the manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Has this article screened for similarity?

Yes

About the License