ISSN: 2581-5989
PubMed - National Library of Medicine - ID: 101738774

International Journal of Dental Science and Innovative Research (IJDSIR)

IJDSIR : Dental Publication Service

Available Online at:www.ijdsir.com

Volume – 8, Issue – 4, August – 2025, Page No. : 211 - 221

Role of Artificial Intelligence in Oral Medicine and Radiology: A Review

[1]Dr. Priya Shandilya, Junior Resident, Department of Oral Medicine and Radiology, BBDCODS, Lucknow

[2]Dr. Deepak U., Professor, Babu Banarasi Das College of Dental Sciences, Lucknow

[3]Dr. Saurabh Srivastava, Reader, Babu Banarasi Das College of Dental Sciences, Lucknow

[4]Dr. Puja Rai, Reader, Babu Banarasi Das College of Dental Sciences, Lucknow

[5]Dr. Ashish Sengar, Junior Resident, Babu Banarasi Das College of Dental Sciences, Lucknow

Corresponding Author: Dr. Priya Shandilya, Junior Resident, Department of Oral Medicine and Radiology, BBDCODS, Lucknow.

Citation of this Article: Dr. Priya Shandilya, Dr. Deepak. U., Dr. Saurabh Srivastava, Dr. Puja Rai, Dr. Ashish Sengar, "Role of Artificial Intelligence in Oral Medicine and Radiology: A Review", IJDSIR- August – 2025, Volume – 8, Issue – 4, P. No. 211 – 221.

Type of Publication: Review Article

Conflicts of Interest: Nil

Abstract

Artificial Intelligence (AI) has emerged as a transformative tool in oral medicine and radiology, enhancing diagnostic accuracy and clinical decision-making. This review explores the role of AI, particularly machine learning (ML) and deep learning (DL), in improving the detection and management of various oral conditions, including jaw lesions, oral squamous cell carcinoma (OSCC), salivary gland disorders, temporomandibular joint (TMJ) disorders, oral potentially malignant disorders (OPMDs), and mandibular fractures. AI-driven models, such as convolutional neural networks (CNNs) and radiomics, have demonstrated high accuracy in identifying maxillofacial cysts, tumors, and TMJ osteoarthritis using imaging modalities like cone-beam computed tomography (CBCT), CT, and MRI. These models often outperform or match experienced radiologists, offering faster, objective, and non-invasive diagnostic support. Additionally, AI facilitates early detection of OPMDs and OSCC by analyzing clinical and imaging data, enabling personalized treatment planning and reducing diagnostic variability. By integrating AI-based clinical decision support systems (CDSS), dental practitioners can achieve improved patient outcomes through enhanced diagnostic precision and efficiency. This review underscores AI's potential to revolutionize oral healthcare while highlighting the importance of expert-annotated datasets and standardized validation processes for developing reliable AI models.

Keywords: Artificial intelligence, AI- oral lesions, OPMDS, OSCC

Introduction and background

The human brain is one of the most fascinating and complex organs, captivating scientists and researchers for decades. Despite ongoing advancements, developing a perfect model that replicates its intricate functions remains a major challenge. Since the introduction of the term artificial intelligence (AI) by John McCarthy in 1956[1], efforts to replicate human cognitive abilities through machines have steadily progressed. Often referred to as the "fourth industrial revolution," AI involves the use of computer technology to simulate human-like reasoning, decision-making, and intelligent behavior [2].

Artificial intelligence

Artificial intelligence (AI) can be defined as the ability of software systems to replicate human cognitive functions[2].

A key subset of AI is machine learning (ML), which involves the use of algorithms to solve various problems, such as data classification and regression. ML has emerged as a powerful tool for researchers aiming to convert large volumes of data into clinically useful knowledge to assist in decision-making[2]. One of the key advantages of ML is that it does not require explicit programming for each task; rather, the system learns patterns from data.

Machine learning can be categorized based on the learning process into the following types:

Supervised Learning: The algorithm is trained using labeled datasets, where the correct output is known and serves as the "ground truth."

Unsupervised Learning: In this approach, the algorithm analyzes unlabeled data to discover hidden patterns or structures, without prior knowledge of expected outcomes.

Reinforcement Learning: Here, the software operates within a dynamic environment and learns through feedback in the form of rewards or penalties based on its actions.

As AI continues to shape the future of healthcare, it becomes increasingly important for current and future dental practitioners to understand its core concepts, working mechanisms, and potential applications in diagnosis—especially within the field of Oral Medicine and Radiology [17].

Early diagnosis of cancer is essential for effective patient management, and AI has demonstrated significant promise in enhancing diagnostic accuracy[20]. Widespread adoption of AI can be further supported by improving practitioners' understanding of disease presentations, risk factors, and symptomatology. This would, in turn, facilitate the identification of early malignant signs that might otherwise go unnoticed or be misinterpreted.

Key risk factors for oral cancers include tobacco and alcohol use, as well as human papillomavirus (HPV) infection, particularly in oropharyngeal cancers. Rigorous control and early detection of these factors play a vital role in prevention and management.

Oral Potentially Malignant Disorders (OPMDs) are defined as "oral mucosal abnormalities associated with a statistically increased risk of malignant transformation"[20]. Early identification of these lesions is critical, as they may progress to oral cancer. Visual screening of the oral cavity remains a widely accepted, effective, and safe method for detecting such lesions, especially in routine clinical practice. It offers a high discriminative capacity and requires minimal time. Recent studies have also explored the role of adjunctive tools such as autofluorescence imaging in mass screening programs. While helpful, these tools are recommended to complement—not replace—conventional oral examination. Oral biopsy continues to be the diagnostic gold standard for OPMDs.

Clinical Decision Support Systems (CDSS) are computer-based tools designed to aid healthcare professionals in clinical decision-making. These systems can assist in diagnosis, preventive care, treatment planning, and prognosis estimation. However, many oral diseases present with overlapping clinical features, despite having diverse etiologies and pathologies. Since treatment decisions and outcomes are directly linked to an accurate diagnosis, a systematic and knowledgeable approach to differential diagnosis is critical [21].

AI-based systems have the potential to overcome diagnostic challenges by analyzing complex data patterns, improving diagnostic consistency, and aiding in clinical training[31]. By mimicking expert-level reasoning in specific domains of knowledge, AI can serve as a valuable tool in oral healthcare—enhancing both patient outcomes and practitioner efficiency [32].

Brief History and Key Concepts of Artificial Intelligence

The term artificial intelligence (AI) was coined in 1955 by mathematician John McCarthy, who is widely regarded as the father of AI. He introduced the term to describe the potential of machines to perform tasks typically associated with human intelligence [1].

In **1956**, McCarthy organized the Dartmouth Conference, which formally launched AI as a research discipline [1]. This event marked the beginning of a significant era of AI development, particularly between the 1950s and 1970s, during which substantial foundational research was conducted.

In 1978**,** applied mathematician Richard Bellman defined AI as "the automation of activities associated with human thinking," such as learning, decision-making, and problem-solving [30].

Today, AI refers broadly to machines or technologies capable of simulating human cognitive functions. To better understand AI, it is important to grasp a few key concepts:

Artificial Intelligence: The capability of machines to exhibit intelligent behavior. The goal is to create systems that can learn from data and solve problems autonomously [2].

Machine Learning (ML): A subfield of AI that uses algorithms to learn from datasets and make predictions or decisions without being explicitly programmed [2].

Neural Networks: A set of algorithms inspired by the human brain, designed to recognize patterns by simulating interconnected neurons that process data.

Deep Learning: A specialized form of ML that uses multiple computational layers within a neural network to analyze data and automatically detect features or patterns[4].

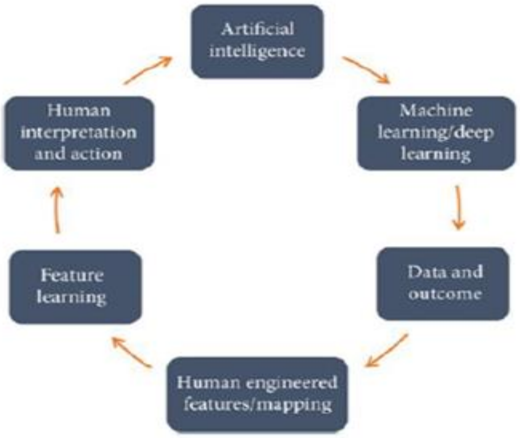

Figure 1: Illustration of artificial intelligence model

These components form the foundation of modern AI systems that are increasingly used across fields, including healthcare and dentistry, to enhance decision-making and improve outcomes [33].

Illustration of artificial intelligence model

How Deep Learning Works: Training, Reference Standards, Validation, and Testing

Deep learning (DL) relies on neural networks composed of multiple layers, each performing a specific task. These layers work iteratively, allowing the system to learn patterns and improve performance over time. The process begins with the creation of a training dataset, usually consisting of a large number of annotated diagnostic images.

The DL model is trained by exposing it to numerous examples of the target object or condition. For example, to train a system to recognize a specific type of bird, thousands of bird images are input into a convolutional neural network (CNN). The network gradually learns to detect the defining features of the bird through repeated exposure and feedback.

Before testing, the model undergoes a validation phase, using a separate dataset—typically similar in size to the test set—to fine-tune its performance and prevent overfitting. Validation ensures that the model has learned from accurate examples, making the choice of reference standards crucial.

Reference Standards in AI Training

To ensure proper learning, training datasets must be labeled with true examples of the condition or object of interest. In dental imaging, for instance, the system must be trained using radiographs that show actual carious lesions, accurately annotated by experts [5].

There are three main types of reference standards used in AI training:

Expert Consensus Panels: The most common approach involves a group of specialists, such as oral and maxillofacial radiologists, who annotate images based on their expertise.

Delphi Method: A more structured approach, this involves multiple rounds of questionnaires among experts to reach a consensus. While this method is more robust, it is also time-consuming and resource-intensive, especially for large datasets. It requires diverse expert representation across specialties and regions. Each image in the training set must be annotated—typically by marking lesions or healthy areas—to guide the model in learning relevant features. For example, to train a model to detect dental caries, radiographs are labeled with bounding boxes around lesions or areas without disease as controls [5].

This comprehensive process—comprising training, validation, expert annotation, and testing—ensures the development of reliable and clinically applicable AI models in fields such as oral and maxillofacial radiology[17].

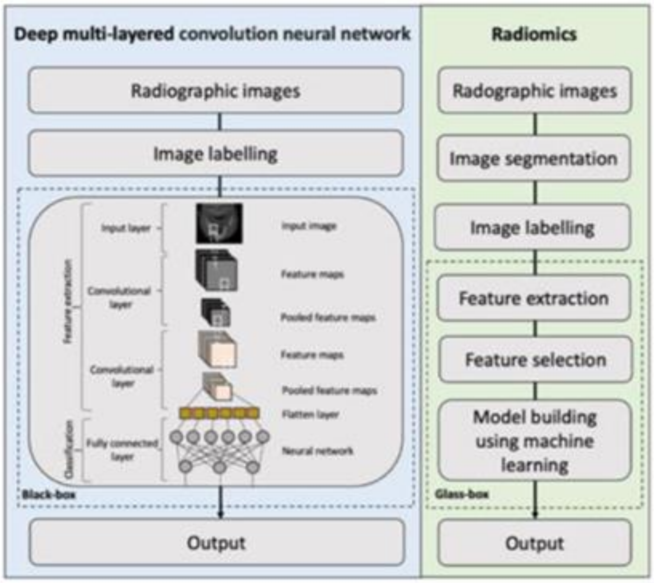

Figure 2: Application of AI in oral medicine and radiology

Application of AI in oral medicine and radiology:

Jaw lesions

Jaw lesions, often incidentally discovered during routine dental radiographic examinations, are commonly cystic and can be difficult to distinguish from tumors. This diagnostic challenge has driven the development of artificial intelligence (AI), particularly deep learning (DL) models, to aid in the automated identification of maxillofacial cysts and tumors on 2D panoramic radiographs [18].

Several studies have focused on lesions such as ameloblastoma, odontogenic keratocysts (OKCs), dentigerous cysts, radicular cysts, and bone cysts, achieving diagnostic accuracies comparable to those of oral and maxillofacial surgeons [4].

More recently, deep learning approaches have also been applied to cone-beam computed tomography (CBCT), which offers superior 3D visualization and quantitative detail compared to panoramic radiographs. For instance, Lee et al. developed convolutional neural network (CNN) models capable of automatic detection, segmentation, and classification of OKCs, dentigerous cysts, and periapical cysts using both panoramic and CBCT images. Their model trained on CBCT data showed superior performance, highlighting CBCT's advantage in depicting lesion morphology in three dimensions [5].

Similarly, Bispo et al. and Chai et al. developed CNN-based systems to distinguish ameloblastoma from OKCs using CT images. Notably, Chai et al.'s model achieved an accuracy of 85%, outperforming both senior and junior oral–maxillofacial surgeons, and delivering results in approximately 3 milliseconds per scan [11].

These advancements underscore the potential of deep learning models to support general dental practitioners in the early identification of jaw cysts and tumors using CBCT, enabling timely referral to specialists and early intervention for better patient outcomes [18].

Oral squamous cell carcinoma (OSCC) is the sixth most common cancer globally and is known for its high invasiveness and frequent cervical lymph node metastasis [6]. Metastasis to cervical nodes significantly worsens prognosis and is closely linked to reduced overall survival. To address the risk of occult metastasis, prophylactic neck dissection is commonly performed in OSCC patients. However, this procedure often leads to severe functional and sensory complications, such as nerve damage and shoulder stiffness, affecting quality of life [6].

Radiomics and Predictive Modeling

Beyond CNNs, radiomics—the extraction of high-dimensional features from imaging data—has shown promise in predicting lymph node metastasis in oral and head and neck cancers [14, 15].

These AI and radiomics models offer significant potential for personalized treatment planning in OSCC, improving early metastasis detection while reducing unnecessary surgical interventions [6].

Salivary gland diseases encompass a variety of inflammatory, infectious, and neoplastic conditions, most commonly affecting the parotid glands, followed by the submandibular, sublingual, and minor salivary glands. Diagnosing these conditions remains challenging in both dentistry and otorhinolaryngology, as it often relies on clinical experience and diagnostic imaging.

Magnetic resonance imaging (MRI) is preferred for its superior soft tissue contrast, and most deep learning (DL) models for salivary gland diagnosis have been developed using MRI data [29]. However, CT imaging is more widely available and continues to play a key role in evaluating neoplasm extent. Applying DL to CT can broaden its clinical application.

Kise et al. developed a CNN model using CT images to detect fatty degeneration in salivary glands—an important marker for Sjögren's syndrome. The model performed comparably to experienced radiologists and better than less experienced ones [7].

DL models have also shown success in differentiating salivary gland tumors.

Yuan et al. developed a CNN to classify pleomorphic adenomas vs. malignant parotid tumors, achieving 90% accuracy [12].

Zhang et al. trained several CNN models to distinguish benign from malignant tumors, with their custom model reaching 98% accuracy, outperforming pre-trained networks like VGG16, InceptionV3, ResNet, and Dense Net [8].

Salivary Gland Tumor

Diagnosing salivary gland disorders—ranging from inflammatory and autoimmune diseases to benign and malignant tumors—is often challenging due to the complex anatomy and subtle imaging features. Artificial intelligence (AI), especially deep learning (DL) and radiomics, has shown promising potential in improving diagnostic accuracy and efficiency [29].

Deep Learning Applications

CT Imaging

Kise et al. developed a CNN model on CT scans to detect fatty degeneration of salivary glands, aiding in the diagnosis of Sjögren's syndrome. The model performed comparably to experienced radiologists and surpassed less experienced ones [7].

CNNs have also been trained to differentiate pleomorphic adenomas from malignant tumors, achieving high accuracy (up to 98%) using both custom and pre-trained networks (e.g., VGG16, ResNet) [8,12].

MRI Imaging:

Although less widely available, MRI-based models show slightly superior performance in soft tissue analysis. CNNs trained on MRI images have successfully classified tumor types such as Warthin tumors and pleomorphic adenomas [29].

Radiomics and Machine Learning

Radiomic analysis involves extracting quantitative features (e.g., texture, shape, intensity) from medical images: Mucoepidermoid carcinoma: High-grade tumors are associated with distinct radiomic features such as irregular surfaces and high texture correlation [13].

Combined models: Integrating radiomic features with clinical data (like lymph node status) using machine learning classifiers (e.g., SVM) improves the differentiation of benign vs. malignant parotid tumors [13].

Clinical Implications

AI-driven models offer:

Non-invasive, faster, and more objective diagnosis

Improved diagnostic support for less experienced clinicians

Potential for early detection and personalized treatment planning

These AI and radiomics models offer valuable clinical decision support, helping practitioners accurately classify salivary gland tumors and identify malignancy risk, potentially leading to earlier and more precise treatment[29].

Primary Sjögren's Syndrome

Characteristics that are specific to the assessment of pSS from SGUS images are: a) high variance of SGs in appearance, shape, and size, and b) low relevance of SGs' surrounding tissues for the diagnosis. Considering the cohort size, and these requirements, we propose a novel radiomics-based procedure as a suitable approach for solving the given problem [7].

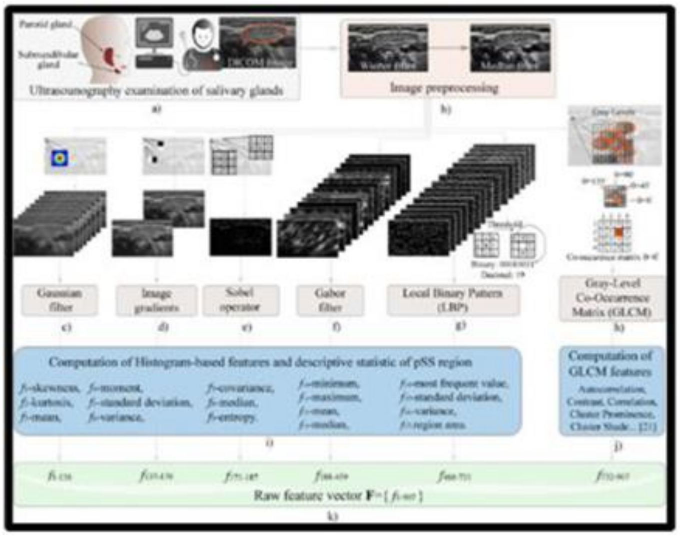

Figure 3:

Figure 3 Overview of the feature extraction procedure. From a segmented SG region, radiomics features were extracted by using: Gaussian filter, image gradients, Sobel operator, Gabor filter, Local Binary Pattern, and Gray Level Co-occurrence Matrix. The raw feature vector F consisted of a total 907 features, which were obtained by varying parameters of the considered feature extractors.

Temporomandibular Joint (TMJ) Disorders

Temporomandibular joint (TMJ) disorders are among the most prevalent orofacial dysfunctions, commonly presenting with symptoms such as clicking sounds, limited jaw movement, pain, and headaches. These disorders are often associated with degenerative changes in the joint, beginning with flattening or sclerosis of the mandibular condyle, progressing to cortical erosion, and potentially leading to osteoarthritis.

Diagnosing TMJ disorders accurately remains difficult, especially for general dental practitioners, as it typically requires significant clinical expertise to avoid misdiagnosis or unnecessary treatments. CBCT (cone-beam computed tomography) is frequently used to evaluate TMJ morphology, but subjective interpretation of CBCT images shows poor consistency among clinicians [9]. This highlights the need for objective, automated diagnostic tools.

Deep Learning in TMJ Assessment

Le et al. developed a convolutional neural network (CNN) model for automatic segmentation of the mandibular ramus and condyle in CBCT images [9].

Kim et al. introduced a CNN-based system that can automatically segment and measure the cortical thickness of the mandibular condyle. The model showed good accuracy with a processing time of around 10 seconds, supporting quantitative analysis of TMJ bone changes [16].

De Dumast et al. designed a DL model that could classify TMJ osteoarthritis into five morphological subtypes based on CBCT images. The model achieved 91% agreement with expert radiologists, demonstrating its clinical potential [9].

Radiomics and Machine Learning Approaches

Bianchi et al. combined radiomic features with clinical, demographic, and biomolecular data to develop diagnostic models for TMJ osteoarthritis. Among the algorithms tested, a model integrating XGBoost and Light GBM yielded the best results, with an AUC of 0.82[10]

These AI-based tools provide a promising pathway toward early detection and standardized assessment of TMJ osteoarthritis, reducing diagnostic variability and enhancing patient outcomes [9].

AI in Detection of Oral Premalignant Disease

AI can play a significant role in OPMD screening by improving risk assessment, enabling earlier detection, and personalizing treatment strategies. AI tools can use unstructured data sources like health records and look at specific prognostic factors such as patient demographics, risk habits, and molecular markers to assess an individual’s risk of developing oral cancer. This allows for more precise intervention, leading to better treatment outcomes and survival rates. Additionally, AI models can analyze clinical photographs and imaging, helping to reduce subjectivity in OPMD assessment and facilitating early detection [20, 24, 25, 26, 27].

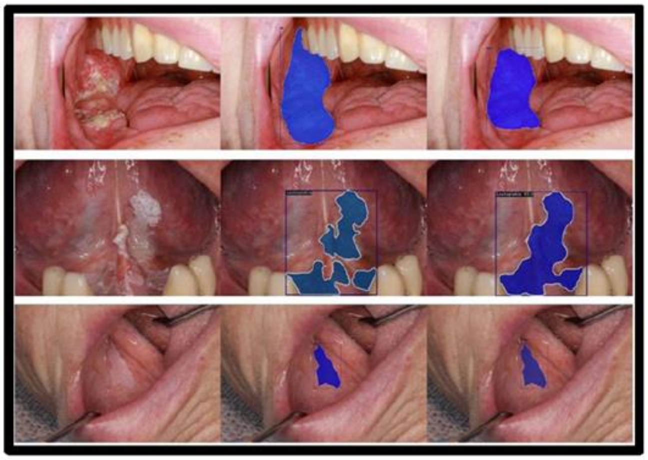

Figure 4: examples of correct OSCC, leukoplakia and OLP predictions, the left column is the input image, the middle column is the reference annotation and right column is prediction.

Mandibular Fractures

The mandible is the only moveable and the most commonly fractured bone of the face in trauma cases. A CNN model was developed to automatically detect mandibular fractures on CT images [16]. The models first generated a synthesized panoramic image from the original CT scan. The mandibular region in the synthesized panoramic image was subsequently straightened and divided into image patches of nine subregions, including symphysis, left/right parasymphysis, left/right mandibular body, left/right mandibular angle, and left/right condylar process. Eventually, the model determined the presence or absence of a fracture on the image patches of specific mandibular subregions. This model achieved high fracture detection accuracy with AUC values of 0.93–0.98 across the nine mandibular subregions, which may be particularly useful for detecting occult condylar fractures [16].

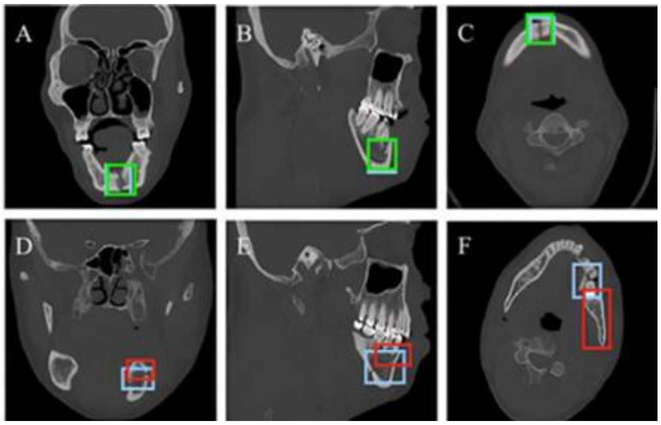

Figure 5: symphysis fracture

Eventually, the model determined the presence or absence of a fracture on the image patches of specific mandibular subregions. This model achieved high fracture detection accuracy with AUC values of 0.93–0.98 across the nine mandibular subregions, which may be particularly useful for detecting occult condylar fractures [16].

Conclusion

Artificial intelligence, particularly through machine learning and deep learning models, is revolutionizing diagnostic practices in oral medicine and radiology. From detecting jaw cysts and tumors to assessing lymph node metastasis, salivary gland diseases, temporomandibular joint disorders, oral potentially malignant disorders (OPMDs), and mandibular fractures, AI has shown promising results in improving diagnostic speed, accuracy, and consistency. Radiomics further strengthens this potential by enabling detailed analysis of medical imaging data to uncover patterns imperceptible to the human eye. Integration of AI into clinical practice offers substantial benefits including early detection, personalized treatment planning, reduced diagnostic variability, and support for less experienced clinicians. However, challenges such as limited access to high-quality annotated datasets, validation across diverse populations, and regulatory approval still need to be addressed[38]. With continued research and technological refinement, AI is poised to become an indispensable tool in the future of oral healthcare.

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