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Detection of Elementary White Mucosal Lesions by an AI System: A Pilot Study

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Abstract: **Aim:** Accurately identifying primary lesions in oral medicine, particularly elementary white lesions, is a significant challenge, especially for trainee dentists. This study aimed to develop and evaluate a deep learning (DL) model for the detection and classification of elementary white mucosal lesions (EWMLs) using clinical images. **Materials and Methods:** A dataset was created by collecting photographs of various oral lesions, including oral leukoplakia, OLP plaque-like and reticular forms, OLL, oral candidiasis, and hyperkeratotic lesions from the Unit of Oral Medicine. The SentiSight.AI (Neurotechnology Co.®, Vilnius, Lithuania) AI platform was used for image labeling and model training. The dataset comprised 221 photos, divided into training (n = 179) and validation (n = 42) sets. **Results:** The model achieved an overall precision of 77.2%, sensitivity of 76.0%, F1 score of 74.4%, and mAP of 82.3%. Specific classes, such as condyloma and papilloma, demonstrated high performance, while others like leucoplakia showed room for improvement. **Conclusions:** The DL model showed promising results in detecting and classifying EWMLs, with significant potential for educational tools and clinical applications. Expanding the dataset and incorporating diverse image sources are essential for improving model accuracy and generalizability.

Keywords: mouth disease; oral keratosis; oral leukokeratosis; oral leukoplakia; Artificial Intelligence (AI); deep learning; oral candidiasis; dental student

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1. Introduction

Diagnosing oral white lesions is complex due to the broad spectrum of conditions they encompass, ranging from benign reactive lesions to potentially serious dysplastic or neoplastic ones. Characteristic features can help distinguish these lesions, but similarities often complicate the diagnosis, necessitating biopsies for confirmation. Establishing a definitive diagnosis is crucial to avoid delays in treating patients with more severe conditions [1,2].

Elementary white mucosal lesions (EWMLs) constitute only 5% of oral pathologies, yet some, such as leukoplakia and lichen planus, carry significant malignant potential (up to 0.5–100%). Therefore, a thorough clinical diagnostic approach is essential to rule out malignancy or premalignancy [3].

The clinical signs of these conditions vary, and only senior oral medicine experts have demonstrated high reliability in distinguishing them. General dentists, especially trainees, may exhibit lower diagnostic accuracies. An AI system tailored to assist dental students and trainees could be a valuable tool in effectively distinguishing EWMLs [3–5].

EWMLs can result from a thickened keratotic layer or the accumulation of non-keratotic material, arising from factors such as local frictional irritation, immunologic reactions, or more serious processes like premalignant or malignant transformation [3].

Frictional hyperkeratosis, a benign lesion, is characterized by epithelial thickening due to chronic irritation, commonly from ill-fitting dental appliances or habitual cheek biting [6]. Oral leukoplakia (OL) presents as a white patch or plaque that cannot be clinically or histologically attributed to other diseases, often associated with irritants like tobacco and alcohol [7]. Oral lichen planus (OLP) is a chronic mucocutaneous disorder believed to be immune-mediated, presenting with various patterns, including reticular and erosive forms [8,9]. Oral lichenoid reactions (OLR) resemble OLP but arise from medications or dental materials [9–11]. Oral condylomas and papillomas are benign HPV-related lesions with whitish growths on the mucosa [12–14]. Oral candidiasis, or thrush, is a fungal infection characterized by forms such as pseudomembranous and hyperplastic [15–17].

Several mobile applications have been proposed to improve the clinical recognition of oral lesions among medical and dental professionals [18,19]. Machine learning (ML), a subset of artificial intelligence (AI), has emerged as a potent tool for supporting diagnostic tasks in various fields, including healthcare and dentistry. Deep learning (DL) is a subset of ML that involves neural networks with many layers [8,9]. These neural networks are designed to automatically learn and extract features from raw data through a process of hierarchical representation [10]. In the context of this study, DL refers to the use of such advanced neural network architectures to analyze and classify clinical images of oral lesions, enabling the model to detect and differentiate between various types of lesions with high accuracy [11]. DL employs multi-layered neural networks, such as convolutional neural networks (CNNs), to discern intricate patterns in data, particularly in complex structures like medical images. CNNs have played a crucial role in detecting a variety of medical conditions, such as breast cancer in mammograms, skin cancer in clinical screenings, and diabetic retinopathy in retinal images. Similarly, in dentistry, CNNs have shown remarkable effectiveness in identifying different conditions like periodontal bone loss, apical lesions, and caries lesions, achieving high levels of accuracy [8,9,12].

AI has transformed medical and dental diagnostics by analyzing and classifying data, enabling precise diagnoses. DL models, especially CNNs, extract features like gradient differences and analyze shape, contour, and pattern, facilitating efficient detection and differentiation of EWMLs [20–25]. The relevance of AI to oral health is profound. By improving early detection of potentially malignant lesions, AI can enable timely interventions and better patient outcomes. The consistency and objectivity of AI analyses reduce variability and enhance diagnostic accuracy, making the diagnostic process more reliable. Moreover, AI tools can streamline workflows, saving time and resources for practitioners and patients. In educational settings, AI aids in training future dental professionals to effectively diagnose and manage various oral conditions. As of today, there is a lack of AI systems tailored to differentiate EWMLs. Our research aims to fill this critical gap in current diagnostic practices by exploring the effectiveness of a deep learning model in detecting and classifying EWMLs from oral images. The central research question driving this study is: How effective is a deep learning model in detecting and classifying EWMLs in oral images? We hypothesize that the model will achieve high accuracy, potentially outperforming traditional diagnostic methods, and effectively assist trainee dentists and dental students in differentiating EWMLs, thereby improving their diagnostic skills and contributing to more accurate clinical outcomes.

2. Materials and Methods

The initial dataset consisted of 231 clinical oral photographs selected from the database of the Oral Medicine Unit at University Hospital "Policlinico Paolo Giaccone" Palermo, Italy.

The study protocol conformed with the ethical guidelines of the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

These photographs were selected from the database during the period from 29 March 2024 to 8 July 2024. The photographs, which had been originally taken prior to this period, were included in the dataset after obtaining informed consent from patients (ethical approval n.12 07/05/2024). The dataset aimed to represent various oral conditions, including oral leukoplakia, striae and reticular figurations, morsicatio buccarum, linea alba, hyperplastic candidiasis, papilloma, and condyloma. Out of these, 10 photos were discarded during the labeling phase, resulting in a final dataset of 221 photos. The discarded photos did not meet the fundamental requirements for accurate lesion detection. Specifically, these images were removed due to issues such as poor focus, inadequate lighting, or repetitive content. These quality concerns were deemed critical to ensure that the dataset used for training and evaluation was of high integrity, thus supporting reliable model performance. These photographs were meticulously categorized after definitive histopathologic diagnoses (when necessary) into five distinct classes, depicting various manifestations of oral mucosal lesions.

The classification comprised 60 images for striate-reticular lesions, 30 for morsicatio buccarum, 24 for linea alba, 39 for leukoplakia, 40 for condyloma-papilloma, and 28 for oral candidiasis (Table 1). To ensure diversity and randomness in the dataset, photographs of both male and female patients were randomly selected.

Table 1. Number of photos per each class, divided into training and validation. Abbreviations: STR/RET, striate-reticular lesions; MB, morsicatio buccarum; LA, linea alba; LEU, leukoplakia; CON/PAP, condyloma–papilloma; CAN, oral candidiasis.

	STR/RET	**MB**	**LA**	**LEU**	**CON/PAP**	**CAN**	
Training	48	24	20	32	32	23	179
Validation	12	6	4	7	8	5	42
Total	60	30	24	39	40	28	221

A Nikon D7200 digital camera, equipped with a 105 mm lens and a macro flash SB-R200, was utilized for capturing the oral mucosal lesions. The resolution of the photographs varied, with dimensions of 6000×4000 and 4800×3200 pixels. A horizontal resolution of 300 dpi and a vertical resolution of 300 dpi were maintained, with a bit depth of 24 and color representation in sRGB. The input images were resized while preserving their original aspect ratio, with the new maximum dimension set to 1024 pixels and the minimum dimension set to 600 pixels. These specifications ensured high-quality images suitable for detailed analysis and classification.

2.1. Labeling Phase

For labeling the photographs in the dataset, a manual annotation process was employed. The image labeling and model training processes were conducted using the SentiSight.AI (Neurotechnology Co.®, Vilnius, Lithuania) web-based tool. Patient privacy was ensured through a confidentiality agreement with Neurotechnology, confirming that images on the SentiSight.AI platform were used only for model training, not shared with third parties, and stored securely. Each photograph underwent a thorough examination by trained professional senior experts in oral medicine. Utilizing a manual annotation process, clinical images were labeled with bounding boxes outlining regions of interest (ROIs) corresponding to specific lesions depicted. These ROIs were subsequently assigned appropriate class identifiers corresponding to the type of oral mucosal lesion present.

In instances where the lesion spanned a significant area, necessitating the delineation of a large region that could potentially include non-relevant elements such as teeth, clinicians opted to create multiple bounding boxes to optimize the utilization of the photograph without introducing undesired elements irrelevant to the lesion. This approach ensured that the model received optimal training data, minimizing the risk of incorporating extraneous information during the training process.

In some cases, clinicians utilized the inversion of image colors (negative) to facilitate the recognition of certain lesions.

2.2. Model Training

The algorithm used for training was Faster R-CNN with ResNet-101, a powerful CNN architecture. This model, with 44.5 million parameters and 347 layers, served as the backbone network for the detection and classification tasks. Pre-trained weights from the MS COCO dataset were utilized to initialize the network, leveraging the rich feature representations learned from a diverse range of objects and scenes. Subsequently, the entire network was fine-tuned on our dataset of oral mucosal lesion images.

The total training time amounted to 60 min and 27 s. For each of the five classes, an 80% random subset (179 photos) served as the training set, while the remaining 20% (42 photos) constituted the validation set. During fine-tuning, a flat learning rate of 10×10^{-3} and a large model size were employed throughout training, ensuring stable convergence while updating the network parameters. The Stochastic Gradient Descent (SGD) optimizer with momentum was utilized for efficient optimization, facilitating rapid convergence towards a locally optimal solution. Additionally, a batch size of one image was used, allowing for dynamic adjustments during training to accommodate variations in image characteristics and lesion manifestations. The selection of the model checkpoint was based on the highest mean average precision (mAP) metric achieved on the validation set, which occurred at 47 min and 22 s (Figure 1). The cross-entropy loss function was used. Regarding the hardware used for training, the SentiSight.AI web-based tool was utilized. It is important to note that the hardware choice does not influence the accuracy of predictions and, therefore, is not relevant to the scientific study. The focus lies on the methodology, algorithms, and data quality rather than the specific hardware configuration. The best model occurred at 47 min and 22 s.

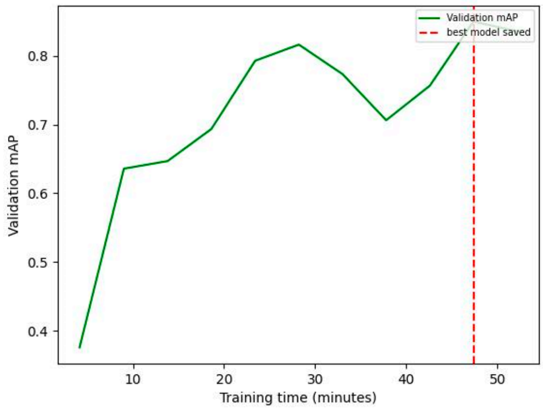

Figure 1. The graph shows the mAP during the training of the Faster R-CNN model with ResNet-101. Initially, the validation mAP is low, but it rises as the model learns. The mAP fluctuates due to the complexity of the data but peaks at 47 min and 22 s, indicating the best model performance. This peak is marked by a dashed red line. After this point, the mAP stabilizes or slightly declines, suggesting that further training may lead to overfitting. In summary, the graph highlights the optimal model performance at 47 min and 22 s, balancing accuracy and generalization.

2.3. Model Validation and Evaluation

The model performance was evaluated on the validation set, which comprised 42 images that were unseen during training, ensuring an independent assessment. A threshold intersection over union (IoU) value of 0.5 was utilized to assess the prediction performance. IoU measures the overlap between the predicted bounding box and the ground truth box, with higher values indicating a closer match. IoU was used to classify predictions as true positive (TP), false positive (FP), and false negative (FN). Specifically, if the predicted bounding box had an IoU $\geq$ 0.5 with the ground truth bounding box, it was considered a TP. Conversely, if the predicted bounding box had an IoU < 0.5 with the ground truth bounding box, it was considered an FP. Additionally, if the ground truth bounding box was not detected by the model, it was considered an FN.

Global metrics for the validation set were computed using precision, sensitivity, F_1 score (harmonic mean of precision and sensitivity, balancing the two metrics), and mAP (Equation (1)).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$F_1\ score = 2 \cdot \frac{Precision \cdot Sensitivity}{Precision + Sensitivity} \tag{3}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{4}$$

Equation (1): Metrics of performance for CNN models. Abbreviations: FN, false negative; FP, false positive; TP, true positive; AP, average precision; mAP, mean average precision.

3. Results

The evaluation of the five-class object detection model was conducted on the validation set. Overall statistics for the entire validation test are summarized in Table 2, while detailed statistics for each class are reported in Table 3. Globally, the model achieved a precision of 77.2%, sensitivity of 76.0%, F1 score of 74.4%, and an mAP of 82.3%. To provide a clearer overview of the results, a confusion matrix was utilized, enabling a more comprehensive understanding of the model's performance in terms of correctly and incorrectly classified instances for each class (Figure 2). Additionally, Table 4 shows the counts of TP, FP, and FN for each class. The confusion matrix provides a detailed overview of the model's performance in correctly classifying different oral lesions in the study. The results show a high accuracy for the striate-reticular lesions, linea alba, and condyloma–papilloma classes, with a value of 1.00, indicating that all images in these classes were classified correctly. The morsicatio buccarum class achieved an accuracy of 0.67, with 0.17 of the images misclassified as striate-reticular lesions and an additional 0.17 not detected. The oral candidiasis class obtained an accuracy of 0.80, with 0.20 of the lesions not detected, while the leukoplakia class showed a lower accuracy of 0.57, with 0.43 of the lesions not detected. This matrix highlights the strengths and critical areas of the model, providing a clearer understanding of the results obtained.

Table 2. Statistics calculated for the whole dataset globally.

Parameter	Value
Precision	77.2%
Sensitivity	76.0%
F_1 *score*	74.4%
mAP	82.3%

Table 3. Statistics calculated for each class individually.

Class	*Precision*	*Sensitivity*	F_1-*Score*	*mAP*
Striae-reticular	54.5%	84.6%	66.3%	62.1%
Morsicatio buccarum	80.0%	66.7%	72.7%	88.9%
Linea alba	80.0%	100.0%	88.9%	90.0%
Leukoplakia	60.0%	25.0%	35.3%	56.8%
Condyloma–papilloma	88.9%	100.0%	94.1%	95.8%
Hyperplasticcandidiasis	100.0%	80.0%	88.9%	100.0%

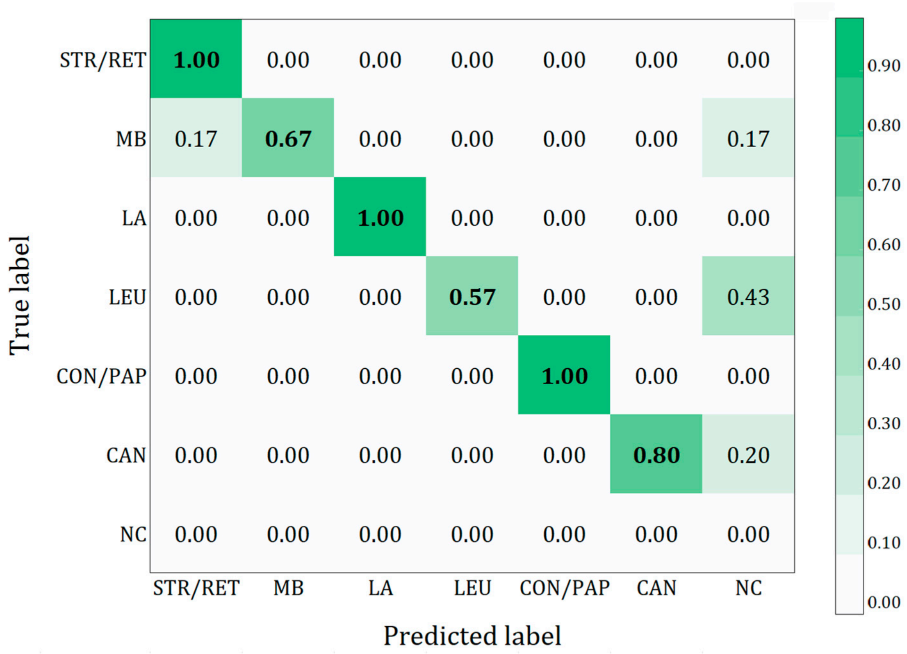

Figure 2. Normalized confusion matrix for multiclass performance. The values on the diagonal represent the *TP*, indicating the proportion of correct classifications for each class. The proportions of misclassifications for each class are shown in the far-right column, labeled as "NC", which represents *FN*. These are cases where the model failed to classify an image into any of the specified classes. The other cells outside the diagonal represent *FP*, where the model incorrectly classified an image as belonging to a particular class when it did not. Abbreviations: STR/RET, striate-reticular lesions; MB, morsicatio buccarum; LA, linea alba; LEU, leukoplakia; CON/PAP, condyloma–papilloma; CAN, oral candidiasis; NC, not classified.

Table 4. Summary of classification counts for multiclass performance. This table shows the counts of *TP*, *FP*, and *FN* for each class.

Class	*TP*	*FP*	*FN*
Striae-reticular	12	0	0
Morsicatio buccarum	4	1	1
Linea alba	4	0	0
Leukoplakia	4	0	3
Condyloma-papilloma	8	0	0
Hyperplasticcandidiasis	4	0	1

4. Discussion

In recent years, there has been significant interest in developing artificial intelligence (AI) systems for computer-aided diagnosis of oral lesions using clinical images. These AI systems, particularly deep learning algorithms, are designed to differentiate malignant oral lesions from benign ones by utilizing various imaging modalities, including clinical photographs and histopathological images [16–20].

AI techniques utilizing CNNs for the diagnosis of diseases have been extensively explored across various fields, particularly in histopathology and dermatology [18–20]. Similarly, in dentistry, the utilization of CNNs shows promise; in fact, AI-based detection in dentistry using clinical photography has demonstrated a high diagnostic odds ratio [18,21].

In this pilot study, we developed object recognition models capable of detecting the presence of EWMLs in images, a task that, while not difficult for an expert dentist, is significant for trainee dentists and dental students.

Several studies have demonstrated the potential of AI-based systems for classifying oral lesions. CNN-based models have shown diagnostic performance comparable to expert clinicians in classifying oral squamous cell carcinoma (OSCC) and oral potentially malignant disorders (OPMDs) using oral photographs [19,20].

To date, however, AI systems enabling the detection and classification of EWMLs are still lacking.

The development of an effective AI system for detecting and diagnosing oral lesions faces several challenges. One of the primary difficulties is obtaining large, diverse, and well-annotated datasets of oral lesion images. Current datasets are often small and limited to specific types of lesions, making it challenging to train robust AI models [22,23]. Additionally, integrating these AI systems into clinical workflows is essential to assist clinicians, especially general practitioners. These systems should improve the accuracy of early cancer diagnosis and support expert-level decision-making in screening programs for oral malignant and potentially malignant lesions. AI functions as a complementary tool rather than a replacement for clinical expertise, reaffirming that dentists remain the key decision-makers in the diagnostic process [24–26].

Another significant challenge is related to the medico-legal issues arising from data privacy concerns and lack of explainability for the systems used [17,27,28].

The performance of CNN models is significantly influenced by image quality and the number of samples [29]. Capturing images of the oral cavity is particularly challenging due to the lack of natural lighting, the need to remove mucous membranes for visibility in certain regions, and difficulties in standardizing angles, distance, framing, and sharpness [30].

The condyloma, papilloma, and hyperplastic candidiasis classes achieved outstanding performance across all statistics, demonstrating the model's ability to distinguish these lesions accurately. High values in some indicators (e.g., precision, sensitivity, F1 score, and mAP) for these classes underscore the robustness and reliability of the model in these areas.

The striae, reticular, and morsicatio buccarum classes show relatively balanced performance, with striae and reticular achieving an impressive sensitivity of 84.6%. This highlights the model's ability to detect these lesions effectively, even if further refinement could enhance precision and reduce false positives.

The leucoplakia class exhibited a precision of 60.0% and a sensitivity of 25.0%. This discrepancy suggests the need for more balanced and representative data for this class to improve the model ability to generalize.

The linea alba class also shows very promising results with a sensitivity of 100.0% and a strong precision of 80.0%. This indicates the efficacy of model capability in detection for this class.

The results highlight how the recognition of linea alba, condyloma, and papilloma lesions is straightforward for AI, as their morphological characteristics are easily distinguishable clinically from other analyzed classes, achieving high values across all statistics.

This study explored the process of gathering and labeling images taken from the oral cavity, specifically those exhibiting confirmed EWMLs by the clinical team. It also showcased the outcomes of using DL to automate the early detection of EWMLs. Our initial findings illustrate promising findings, indicating that DL methods could be effective in addressing this complex challenge. However, some questions are open; first of all, who should perform the image segmentation by designating the bounding boxes useful for model training. Furthermore, it is important to understand whether it is necessary to instruct oral medicine professionals in image segmentation. In our opinion, this training could also benefit dental trainees and dental students by helping them learn to recognize lesions and learn from them. The integration of DSLR photographs into this study might raise concerns about the applicability and future scalability of the AI model in real-world contexts. Although DSLRs provide high-quality images, it is likely that smartphone photos will become more prevalent in the future, especially with the development of apps for diagnosing oral lesions. However, smartphone images can vary in quality due to differences in models, camera specifications, lighting conditions, and user handling, which could impact AI performance if not trained on a diverse dataset [4,31–33].

To date, there are no studies comparing the performance of AI systems with images acquired from DSLRs and smartphones. Therefore, it is crucial to expand datasets with smartphone images to enhance the model's generalization in real-world scenarios, such as screening programs or field diagnostics.

5. Limitations and Strengths

The deep learning models developed for detecting EWMLs have initially yielded satisfactory results, with overall outcomes being quite promising. Nevertheless, a significant limitation is the relatively small size of the dataset, which presents a considerable challenge during the model training phase. Although the model performs well across several classes, there are specific areas that require further improvement. To enhance the model's robustness and generalizability, additional research with larger datasets is necessary.

The study highlights several notable strengths. The use of a Faster R-CNN with ResNet-101 architecture, one of the most advanced models available, showcases a sophisticated application of AI in oral medicine diagnosis. Another strength lies in the high-performance metrics achieved for certain lesion classes, such as condyloma, papilloma, and hyperplastic candidiasis. Additionally, the study suggests that AI-based tools could be especially valuable for training dental students and trainees, enhancing their ability to recognize and understand lesions. This educational aspect could improve training programs and support the development of diagnostic skills. Another interesting aspect of this work is the innovative use of image color inversion (negative), employed in certain cases to enhance the recognition of specific lesions.

6. Conclusions

The challenge of precise lesion localization in object detection can be addressed by expanding datasets, as larger datasets improve deep learning models' ability to detect complex patterns and enhance generalizability. Image augmentation techniques like rotation, scaling, and color adjustments can further enhance model robustness. Incorporating images from various devices ensures adaptability to different image qualities and lighting conditions, while regular updates and user feedback help improve model accuracy. Today, there is a noticeable lack of apps that could facilitate the learning path for trainee dentists and dental students, and developing such applications in the future would be beneficial. Additionally, this tool could potentially be extended to identify red, pigmented, and red-and-white lesions. Early exposure to AI systems in dental education is crucial, as it will prepare students to integrate these technologies into future practice. Future research should focus on developing automatic segmentation tools to streamline image annotation, enhancing scalability and efficiency. While AI can assist in lesion detection, dentists are the ultimate decision-makers in diagnosis, ensuring that AI serves as a complementary tool rather than a replacement for their clinical expertise.

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