Artificial Intelligence in
Medical Imaging

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AIMS AND SCOPE

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INDEXING/ABSTRACTING

There is currently no indexing.

RESPONSIBLE EDITORS FOR THIS ISSUE

Application of machine learning in oral and maxillofacial surgery

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Abstract

Oral and maxillofacial anatomy is extremely complex, and medical imaging is critical in the diagnosis and treatment of soft and bone tissue lesions. Hence, there exists accumulating imaging data without being properly utilized over the last decades. As a result, problems are emerging regarding how to integrate and interpret a large amount of medical data and alleviate clinicians' workload. Recently, artificial intelligence has been developing rapidly to analyze complex medical data, and machine learning is one of the specific methods of achieving this goal, which is based on a set of algorithms and previous results. Machine learning has been considered useful in assisting early diagnosis, treatment planning, and prognostic estimation through extracting key features and building mathematical models by computers. Over the past decade, machine learning techniques have been applied to the field of oral and maxillofacial surgery and increasingly achieved expert-level performance. Thus, we hold a positive attitude towards developing machine learning for reducing the number of medical errors, improving the quality of patient care, and optimizing clinical decision-making in oral and maxillofacial surgery. In this review, we explore the clinical application of machine learning in maxillofacial cysts and tumors, maxillofacial defect reconstruction, orthognathic surgery, and dental implant and discuss its current problems and solutions.

Key Words: Radiography; Artificial intelligence; Machine learning; Deep learning; Oral surgery; Maxillofacial surgery

Core Tip: A dramatic increase in medical imaging data has exceeded the ability of clinicians to process and analyze, which calls for higher-level analytic tools. Machine

learning-based image analysis is useful for extracting key information to improve diagnostic accuracy and treatment efficacy. In this review, we summarize the applications of machine learning in oral and maxillofacial surgery as well as its current problems and solutions.

INTRODUCTION

The oral and maxillofacial region is extremely complex, including many critical anatomical structures such as the maxillofacial bone, parotid gland, facial nerve, and major vessels. Computed tomography (CT), magnetic resonance imaging (MRI; an imaging technique mainly used for the examination of soft tissue), and other radiological examinations are commonly applied to improve the understanding of the three-dimensional spatial positional relationships among these anatomical structures. It is unavoidable to face rapid growth in the amount and complexity of medical imaging data, leading to increased workload for clinicians[1-2].

In recent years, artificial intelligence (AI) has been implemented in medicine to explore these enormous datasets and extract key information[1,3]. AI is a field focused on completing intellectual tasks normally performed by humans, and machine learning (ML) is one of the specific methods of achieving this goal[4]. AI models based on ML algorithms have demonstrated excellent performance in imaging data extraction and analysis and have increasingly matched specialist performance in medical imaging applications[5]. The integration of ML in oral and maxillofacial surgery has been proved to improve diagnostic accuracy, treatment efficacy, and prognostic estimation and reduce health care costs[6,7]. The purpose of this review is to explore the clinical application of ML in maxillofacial cysts and tumors, maxillofacial defect reconstruction, orthognathic surgery, and dental implant and discuss the current problems and solutions.

Arthur Samuel[6-8] first described the term ML in 1952. ML is a technique to build prediction outcomes by statistical algorithms learning from experience. According to the training types of the algorithms, ML can be divided into three categories: Supervised, unsupervised, and reinforcement learning[9]. Currently, supervised learning is the most commonly used training style in medical image analysis[10].

In supervised learning, labels are inputted simultaneously with the training data and then algorithms predict the known outcome[10]. Examples of supervised learning methods include classic Naive Bayes, decision tree (DF), support vector machine (SVM), random forest (RF), logistic regression, artificial neural network (ANN), and deep learning (DL). Specifically, SVM results in data classification by setting up an imaginary high-dimensional space and then separating labeled samples by a hyperplane[4,11]. RF is an extension of DF, in which each DF is independently trained and subsequently combined with others[4,12]. ANN has one hidden layer in addition to the input and output layer. Each layer is composed of neurons and sequentially stacked one after the other *via* weighted connections. The signals are transformed among neurons from the previous layer to the next and DL is comprised of multi-layered ANN[13].

In unsupervised learning[10], the algorithm system will not be provided with labels but depends on itself for the detection of the hidden patterns in the data. Examples of algorithms of unsupervised learning include K-means, affinity propagation, and fuzzy C-means systems. Besides, reinforcement learning[14] holds a system including unlabeled data, agent, and environment. It aims to repeatedly optimize parameters based on environmental feedback through reward and punishment mechanisms. By accumulating the rewards, the models can keep adapting to the changing environment and obtaining the best return. Examples of reinforcement learning algorithms include Maja and Teaching-Box systems.

The protocol of ML comprises data procession and model construction, and the workflow of the model construction can be further divided into the training phase and

the validating/testing phase. Due to the impact of data volume and quality on the performance of machine-learning models, raw data should be standardized in advance for the following aspects: (1) Reducing noise without losing the important features [15]; (2) Splitting the image into parts and delineating the region of interest; and (3) Accumulating enough data[16]. Effective methods have been proposed for achieving the tasks, including image denoising, segment, and augment[15,17-20].

APPLICATION IN ORAL AND MAXILLOFACIAL SURGERY

Maxillofacial cystic lesions and benign tumors

Maxillofacial cysts and benign tumors are common lesions in the oral and maxillo-facial region. In most cases, maxillofacial cysts and benign tumors cause facial swelling, tooth displacement, large bone cavity, and even pathological fracture when diagnosed. Surgery is the only treatment option, including enucleation, decompre-ssion, and resection. And the choice of treatment modality is based on the final diagnosis, lesion size, and age of selected patients. However, these lesions are asymptomatic at the early stage. Consequently, early detection and diagnosis of maxillofacial cysts and benign tumors are crucial for avoiding serious surgery and achieving satisfactory treatment outcomes[21,22]. Numerous studies have demon-strated the usefulness of ML in early screening, accurate diagnosis, proper treatment, and morbidity prevention in maxillofacial cysts and benign tumors.

Frydenlund *et al*[23] applied two ML classifiers (a SVM and bagging with logistic regression) to distinguish among lateral periodontal cysts, odontogenic keratocysts, and glandular odontogenic cysts in hematoxylin and eosin-stained digital micro-graphs. The results proved the effectiveness of the ML-based classifiers in predicting these three types of odontogenic cysts (96.2% correct classification for both classifiers). Moreover, Okada *et al*[24] demonstrated the usefulness of a semiautomatic computer-aided diagnosis framework to differentiate between periapical cysts and granulomas in cone-beam CT (CBCT) data. And the 94.1% best accuracy was yielded with the integration of graph-based random walks segmentation and ML-based boosted classi-fication algorithms. Similarly, Endres *et al*[25] compared the performance of the DL algorithm with that of 24 oral and maxillofacial surgeons in detecting periapical radiolucencies in panoramic radiographs, demonstrating the reliable diagnoses of ML algorithms in dentistry. In addition, Kwon *et al*[26] developed a deep convolution neural network (DCNN) to automatically diagnose jaw odontogenic cysts and tumors in panoramic images, showing higher diagnostic sensitivity, specificity, and accuracy with augmented datasets. Liu *et al*[27] applied deep transfer learning to classify ameloblastoma and odontogenic keratocyst in panoramic radiographs and achieved an accuracy of 90.36%. Yang *et al*[28] also showed that the diagnostic performance of CNN You OnlyLook Once v2 was similar to that of experienced dentists in detecting odontogenic cysts and tumors on panoramic radiographs.

Maxillofacial malignant tumors

Oral cancer is the most common malignancy in the oral and maxillofacial region, which can exert a severe impact on the survival and quality of life of the patients[29]. The most effective method for reducing mortality rates is early detection. However, the optimal strategy for early screening remains debated. The advent of high-quality ML provides potential to improve early diagnosis, prognostic evaluation, and accurate prediction of treatment associated toxicity in oral cancer patients.

Aubreville *et al*[30] presented a novel automatic identification of oral squamous cell carcinoma (OSCC) in confocal laser endomicroscopy images, using a deep ANN. The accuracy of this deep ANN-based method was 88.3%, with a sensitivity of 86.6% and specificity of 90%. It outperformed textural feature-based classification. DL algorithms, including the DenseNet121 and faster R-CNN algorithm, have also been applied to automatically classify and detect oral cancer in photographic images, achieving acceptable precision[31]. Furthermore, Kar *et al*[29] and Jeyaraj and Samuel Nadar[32] developed regression-based partitioned CNN using hyperspectral image datasets for automated detecting oral cancer, obtaining improved quality of diagnosis compared to traditional image classifiers including the SVM and the deep belief network.

In addition, ML has also been applied to predict cancer outcomes using the following prognostic variables: (1) Histological grade; (2) Five-year survival; (3) Cervical lymph node metastases; and (4) Distant metastasis. Ren *et al*[33] included 80 patients finally diagnosed with OSCC and performed ML-based MRI texture analysis using a minimum-redundancy maximum-relevance algorithm, achieving the best

performance with an accuracy of 86.3%. Others also concluded that the predictive performance of DL-based survival prediction algorithms exceeded that of conventional statistical methods[34-38]. Chu *et al*[17] and Ariji *et al*[39] have achieved a DL accuracy of extranodal extension of 84% on 703 CT images. The diagnostic performance outranked that of radiologists. Others also proved the effectiveness of ML in predicting lymph node metastasis in patients with early-stage oral cancer and thus guiding proper treatment plans[32,40,41]. Keek *et al*[42] found that compared with peritumoral radiomics based prediction models, a clinical model was useful for the prediction of distant metastasis in oropharyngeal cancer patients.

ML also contributes to the evaluation of treatment complications. Chu *et al*[17] and Men *et al*[43] have introduced a 3D residual CNN for the prediction of xerostomia in patients with head and neck cancer and achieved satisfying performance with an area under the curve value of 0.84 (0.74-0.91), an index for reflecting the authenticity of the detection method (the closer the numerical value to 1.0, the higher the authenticity of the detection method).

Nasopharyngeal carcinoma is a malignancy of the head and neck, and radiotherapy is the primary treatment option for the suffered patients[44]. To avoid unnecessary toxicities derived from radiotherapy, radiation oncologists propose the concepts of precise radiotherapy and adaptive radiotherapy. Recently, advanced ML techniques have mainly been applied to auto-recognition, early diagnosis, target contouring, and complication prediction in patients with nasopharyngeal carcinoma[45].

Li *et al*[46] developed an endoscopic image-based model to detect nasopharyngeal malignancies. And this DL model outperformed experts in detecting malignancies. Du *et al*[47] investigated the diagnostic performance of seven ML classifiers cross-combined with six feature selection methods for distinguishing inflammation and recurrence based on post-treatment nasopharyngeal positron emission tomography/X-ray CT images (a high-level imaging method that can make an early diagnosis of tumors) and identified the optimal methods in the diagnosis of nasopharyngeal carcinoma.

Lin *et al*[48] constructed a 3D CNN on MRI data sets and validated the performance of automated primary gross tumor (GTV) contouring in patients with nasopharyngeal carcinoma, demonstrating improved contouring accuracy and efficacy with the assistance of a DL-based contouring tool. Men *et al*[49] proposed an end-to-end deep deconvolutional neural network for segmentation of nasopharyngeal carcinoma in planning CT images, showing a high-level performance than that of the VGG-16 model in the segmentation of the nasopharynx GTV, the metastatic lymph node GTV, and the clinical target volume. In addition, Liang *et al*[44] developed a fully automated DL-based method for the accurate detection and segmentation of organs at risk in nasopharyngeal carcinoma CT images and achieved excellent performance. The results showed a sensitivity of 0.997 to 1 and specificity of 0.983 to 0.999. For early detecting the radiotherapy complication in nasopharyngeal carcinoma patients, Zhang *et al*[50] applied the RF method to early predict radiation-induced temporal lobe injury (RTLI) based on MRI examinations. The results demonstrated that the RF models can successfully predict RTLI in advance, which can allow clinicians to take measures to stop or slow down the deterioration of RTLI.

Altogether, ML techniques have been shown well-performed in early screening and prognosis evaluation of maxillofacial malignant tumors.

Maxillofacial bone defect reconstruction

Maxillofacial bone defects after congenital deformities, trauma, and oncological resection greatly decrease patients' quality of life. The goal of reconstruction of maxillofacial bone defects is to restore optimal function and facial appearance using free tissue, vascularized autogenous bone flap transplantation, or prostheses. Maxillofacial reconstructive surgery remains challenging, especially in the cases of massive maxillofacial bone defects across the midline. Most recently, ML algorithms have achieved major success in virtual surgical planning and thus posed great potential in the reconstruction of facial defects.

Jie *et al*[51] proposed an iterative closest point (ICP) algorithm based on normal people database (a database comprised of normal and healthy adults) to predict the reference data of missing bone and performed symmetry evaluation between the postoperative skull and its mirrored model. The result showed that the ICP model achieved similar accuracy to that of navigation-guided surgery. Dalvit Carvalho da Silva *et al*[52] combined CNN with geometric moments to identify the midline symmetry plane of the facial skeleton from CT scans, which aided the surgeons in the maxillofacial reconstructive surgery.

With the development of an imaging database, ML is a promising tool to assist the maxillofacial bone defect reconstruction.

Orthognathic surgery

Orthognathic surgery is used for the treatment of dental malocclusion, facial deformities, and obstructive sleep apnea to improve facial aesthetics and function. Traditionally, surgical planning is based on clinical examination, two-dimensional cephalometric analysis, and manually made splints. However, these procedures require considerable labor efforts and lack precision[53-56]. With the rapid development of technologies and materials, 3D printers, digital software, and ML are increasingly used in orthognathic surgery and greatly improve surgical outcomes. Hence, the applications of ML are promising in orthognathic surgery.

According to the study of Shin *et al*[57], the authors extracted the features from posteroanterior and lateral cephalogram and evaluated the necessity for orthognathic surgery using DL networks. The results showed that the accuracy, sensitivity, and specificity were 0.954, 0.844, and 0.993, respectively, proving the excellent performance. Lin *et al*[58] used a CNN with a transfer learning approach on 3D CBCT images for the assessment of the facial symmetry before and after orthognathic surgery. In a retrospective cohort study, Lo *et al*[59] first applied a ML model based on the 3D contour images to automatically assess the facial symmetry before and after orthognathic surgery. According to the study by Knoops *et al*[60], a 3D morphable model, a ML-based framework involving supervised learning, was trained with 4216 3D scans of healthy volunteers and orthognathic surgery patients. The model showed high diagnostic accuracy with a sensitivity of 95.5% and specificity of 95.2%, satisfying treatment simulation. In addition, Patcas *et al*[61] demonstrated that patients' facial appearance and attractiveness improved after orthognathic surgery using a CNN model.

To sum up, ML has been considered a useful tool in orthognathic surgery for establishing a precise diagnosis, evaluating surgical necessity, and predicting treatment outcomes.

Dental implant

The dental implant has been considered a reliable treatment option for the replacement of missing teeth. Undoubtedly, an excellent bone environment and implant planning are key to the success rate of dental implants. It is crucial to have a basic understanding of the quality and quantity of bone at the planned site and site of placement[62]. In recent decades, ML is growing in the field of dental implants and its use has been applied to improve the success rate of implants and identify dental implants.

Kurt *et al*[63] applied a DL approach on three-dimensional CBCT images to perform implant planning and compared the performance of this method with manual assessment, achieving similarly acceptable results in the measurements in the maxilla molar/premolar region, as well as in the mandible premolar region. A pilot study by Ha *et al*[64] demonstrated that the mesiodistal position of the inserted implant is the most significant factor predicting implant prognosis using ML methods.

Besides, Lee *et al*[65] evaluated the performance of three different DCNN architectures for the detection and classification of a fractured dental implant using panoramic and periapical radiographic images. The results showed the best performance by the automated DCNN architecture based on only periapical images. Mameno *et al*[66] applied three ML methods for the prediction of peri-implantitis and analyzed the risk indicators. RF model achieved the highest performance in the prediction. And the results demonstrated that implant functional time influenced most on prediction.

In addition, several investigations proved the effectiveness of ML methods for implant type recognition using radiographic images[67-69]. As for the application of ML models for implant design optimization, Roy *et al*[70] used an ANN combined with genetic algorithms for the prediction of the optimum implant dimension.

ML models have demonstrated great potential in the field of dental implants for assisting implant planning, evaluating implant performance, improving implant designs, and identifying dental implants.

PROBLEMS AND SOLUTIONS

ML has shown great potential in the field of oral and maxillofacial surgery for

Table 1 Machine learning applications in oral and maxillofacial surgery

Ref.	Applications	Purpose	Method
[23]	Maxillofacial cystic lesions and benign tumors	Accurate diagnosis	A support vector machine and bagging with logistic regression
[24]			Integration of graph-based random walks segmentation and machine learning-based boosted classification algorithms
[26]			Deep convolution neural network
[27]			Deep transfer learning
[28]			Convolution neural work You OnlyLook Once v2's
[25]		Early detection	Deep learning
[30]	Maxillofacial malignant tumors	Early diagnosis	Deep artificial neural network
[31]			Deep learning (DenseNet121 and faster R-Convolution neural work)
[29, 32]			Regression-based partitioned convolution neural network
[46]			Deep learning
[47]			Machine learning
[48]		Early detection	Convolution neural network
[49]			End-to-end deep deconvolutional neural network
[44]			Deep learning
[33]		Prognosis estimation	Minimum-redundancy maximum-relevance algorithm
[34-39]			Deep learning
[40-42]			Machine learning
[43]		Treatment complication evaluation	Convolution neural network
[50]			Random forest
[51]	Maxillofacial bone defect reconstruction	Missing bone prediction and facia symmetry evaluation	Iterative closest point
[52]		Midline symmetry plane identification	Convolution neural network
[57]	Orthognathic surgery	Surgery necessity evaluation	Deep learning
[58]		Facial symmetry assessment	Convolution neural network
[59]			Machine learning
[60]		Diagnosis	Machine learning
[61]		Facial appearance and attractiveness evaluation	Convolution neural network
[63]	Dental implant	Implant planning designing	Deep learning
[70]		Implant planning optimizing	Artificial neural network
[64]		Prognosis estimation	Machine learning
[65]		Detection and classification of fractured dental implant	Deep convolution neural network
[66]		Complicationprediction	Machine learning
[67-69]		Implant type recognition	Machine learning

improving detection accuracy, optimizing treatment plans, and providing reliable prognostic prediction. Despite all the potential, there still exist some limitations.

First, the performance of ML mainly depends on the volume and quality of data and superior algorithms. The scattered distribution of dental databases across healthcare settings often leads to the problem of relatively small datasets, exerting an impact on real clinical decision-making. Efforts should be made for the development of cloud-

based image databases and large open-access databases from diverse settings and populations[71].

Second, it is quite difficult for ML to analyze a large number of different and heterogeneous datasets. A set of well-standardized, segmented, and enhanced training data will enhance the performance of the ML model. Thus, the involved data should get properly pre-processed for maximally achieving homogenization of the data sets and reducing errors[15,17,72].

Third, the performance of ML algorithms in completing various common clinical tasks is similar to or outmatches that of experts. However, when dealing with cases of rare and complicated diseases, existing algorithms may have inferior performance[73, 74]. Consequently, further improvement of ML algorithms is required for computing enormous and complex medical data.

Lastly, there exist many ethical challenges, including privacy protection, data security, and legal and regulatory issue. Patients' informed consent has to be obtained before using their clinical data for ML. Moreover, relevant guidelines should be developed for data acquisition and data sharing. Meanwhile, data should be transparent and traceable without the disclosure of personal information. Strict legal requirements should be made regarding health data privacy.

CONCLUSION

ML will have an immense impact in the field of oral and maxillofacial surgery in the following aspects. First, ML is useful in early screening, accurate diagnosis, proper treatment, morbidity prevention, and accurate prediction of treatment associated toxicity in the treatment of maxillofacial cysts, benign tumors, and malignant tumors. Second, ML algorithms have achieved major success in virtual surgical planning and thus posed great potential in the reconstruction of facial defects. Third, ML has been considered a useful tool in orthognathic surgery for establishing a precise diagnosis, evaluating surgical necessity, and predicting treatment outcomes. Lastly, ML models have demonstrated great potential in the field of dental implants for assisting implant planning, evaluating implant performance, improving implant designs, and identifying dental implants (Table 1).

Nonetheless, it remains vital to evaluate the reliability, accuracy, and repeatability of ML in medicine. Further studies should continually focus on improving the usability of algorithms for different diseases. Moreover, there exists an urgent need to develop guidelines for many ethical challenges, including privacy protection, data security, and legal and regulatory issue. Despite these issues, ML is still considered to be a powerful tool for clinicians. We believe that this review may provide detailed information regarding ML applications in oral and maxillofacial surgery and help assist clinicians to facilitate the clinical practices.

ACKNOWLEDGEMENTS

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Pictorial research of pancreas with artificial intelligence and simulacra in the works of Fellini

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Abstract

This is the consideration recalled from my reading of *Acute pancreatitis: A pictorial review of early pancreatic fluid collections* by Xiao. This perspective related to the works of Fellini might be able to contribute the future development of the research of pancreatic diseases.

Key Words: Pancreatic diseases; Medical imaging; Artificial intelligence; Baudrillard; Simulacra; Fellini

Core Tip: This paper offers, so to speak, a new postmodernist view of medicine. Particularly in medical imaging, where phenomena are observed in pictorial ways, research engaging with art and epistemology will be essential in the future. It will also go hand in hand with the use of artificial intelligence. Although philosophical discourse has not been greatly used in clinical research, the rapid development of psychopathology and medical philosophy suggests that such research will be needed in these fields. This thought was inspired by an article in this journal; therefore, it is most appropriate that it should be published in this journal.

TO THE EDITOR

This is what I have considered since I read the article *Acute pancreatitis: A pictorial review of early pancreatic fluid collections* by Xiao[1]. This consideration is related with

the works of Fellini, as follows:

REALITIES OF DEFINING CHARACTERISTIC

In the works of Fellini, a predominant concept is the concept of precapitalist consciousness. In a sense, Marx uses the term 'dialectic socialism' to denote the common ground between sexual identity and society.

"*Truth is meaningless*," says Foucault; however, according to Bailey[2], it is not so much truth that is meaningless, but rather the defining characteristic, and some would say the failure, of truth. The main theme of Parry[3]'s model of the postconceptual paradigm of reality is the role of the writer as artist. But if the deconstructivist theory holds, we have to choose between dialectic socialism and Sartreist existentialism.

The primary theme of the works of Fellini is a subcapitalist reality. In a sense, Lyotard uses the term 'semioticist narrative' to denote the difference between society and class.

Any number of deconstructions concerning dialectic socialism exist. But Sartre promotes the use of the postconceptual paradigm of reality to modify society.

The main theme of Pickett[4]'s critique of dialectic socialism is the economy, and therefore the paradigm, of pretextual class. It could be said that Foucault uses the term 'Baudrillardist simulacra' to denote a mythopoetical whole.

An abundance of narratives concerning the role of the participant as artist may be discovered. But the subject is contextualized into a dialectic socialism that includes art as a paradox.

MATERIAL RATIONALISM AND SUBCULTURAL DEAPPROPRIATION

If one examines dialectic socialism, one is faced with a choice: either reject capitalist libertarianism or conclude that sexual identity, perhaps ironically, has intrinsic meaning. Subcultural deappropriation implies that consensus is a product of the masses, but only if the premise of dialectic socialism is valid. Thus, several narratives concerning neomodern capitalist theory exist.

The primary theme of the works of Fellini is a self-sufficient totality. The main theme of Hernández[5] is an analysis of subcultural deappropriation as the common ground between narrativity and society. It could be said that Derrida uses the term 'dialectic socialism' to denote not discourse as such, but postdiscourse.

The subject is interpolated into a subcultural deappropriation that includes culture as a whole. Therefore, a number of theories concerning a subconstructive reality may be found.

The primary theme of the works of Fellini is the bridge between truth and sexual identity. However, the subject is contextualised into a dialectic rationalism that includes reality as a paradox.

Geoffrey[6] holds that we have to choose between dialectic socialism and postdialectic textual theory. In a sense, in La Dolce Vita, Fellini denies substructuralist nationalism; in Amarcord he affirms subcultural deappropriation.

CONCLUSION

Though mentioned above is my perspective recalled from Xiao's article, it pertains to research on applying pictorial ways to the research of pancreatitis and other pancreatic diseases. This perspective concerning the works of Fellini might be able to contribute to the future development of the research field.

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