International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 4, Number 1, Year 2024
DOI: https://doi.org/10.62051/ijcsit.v4n1.31
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research on the Design of Medical Imaging Assisted Diagnosis System Based on Machine Learning

Xinzhe Yuan

Northeastern University, Boston, Boston, Massachusetts, USA

ABSTRACT

The design and application of medical imaging diagnostic assistance systems have become an indispensable facet of modern medicine. Technologies based on machine learning can handle vast and intricate medical imaging data, offering precise diagnostic support and significantly enhancing the efficiency and accuracy of clinical diagnoses. This study focuses on the development and implementation of an efficient medical imaging diagnostic assistance system utilizing machine learning algorithms such as Principal Component Analysis (PCA), Support Vector Machines (SVM), and Multi-Layer Perceptrons (MLP). Through the architectural design of intelligent diagnostic assistance systems, data preprocessing, and feature vectorization, combined with the application of classification algorithms, a robust diagnostic support system capable of addressing diverse medical scenarios has been constructed. Performance evaluation experiments indicate that this system demonstrates high accuracy and robustness in processing medical imaging data, holding potential for clinical implementation. The findings of this study provide new insights for the advancement of intelligent diagnostic systems in medical imaging and lay a solid foundation for the development of future clinical diagnostic tools.

KEYWORDS

Machine learning; Medical imaging; Assisted diagnosis; System design

1. INTRODUCTION

With the continuous advancement of medical imaging technology, the variety and volume of imaging data have experienced an explosive growth, presenting unprecedented challenges and opportunities for medical diagnosis. Traditional manual diagnosis relies on the expertise and experience of physicians, yet efficiency and accuracy often become difficult to ensure when confronted with vast and complex imaging data. Consequently, machine learning techniques have increasingly been introduced into the realm of medical imaging analysis, significantly enhancing the efficiency and precision of image diagnosis through automated feature extraction and classification algorithms. This study aims to explore and design a machine learning-based medical imaging diagnostic support system, focusing on the application of classification technologies such as Principal Component Analysis, Support Vector Machines, and Multi-Layer Perceptrons in processing imaging data. By investigating the architecture and data processing workflow of intelligent diagnostic support systems, this research seeks to develop a system capable of meeting clinical needs and experimentally validate its performance. This study not only contributes to advancing the intelligence of medical imaging analysis but also offers new methods and perspectives for the efficient processing and analysis of future medical imaging data.

2. MACHINE LEARNING BASED CLASSIFICATION TECHNIQUES

2.1. Principal Component Analysis

Principal Component Analysis (PCA) is an important statistical method that is widely used for data reduction and feature extraction in machine learning. The core idea of PCA is to project the original high-dimensional data into a low-dimensional space by linear transformation, so as to reduce the number of variables while retaining the main information of the data as shown in Figure 1. shown. This process is done by finding the directions in the data that have the highest variance, i.e., the principal components, which allows these principal components to maximize the retention of the variability of the original data. In medical image analysis, the dimensionality of the data is usually very high and contains a large number of interrelated variables, such as different pixel values, gray scale distributions, and texture features. Such high-dimensional data not only increase the computational complexity, but also may lead to the overfitting problem of the model. Therefore, the application of PCA in medical image processing is particularly important [1]. Through PCA, these high-dimensional features can be effectively compressed into a small number of principal components, which largely retain the main features of the original data, thus simplifying the subsequent classification and diagnosis process.

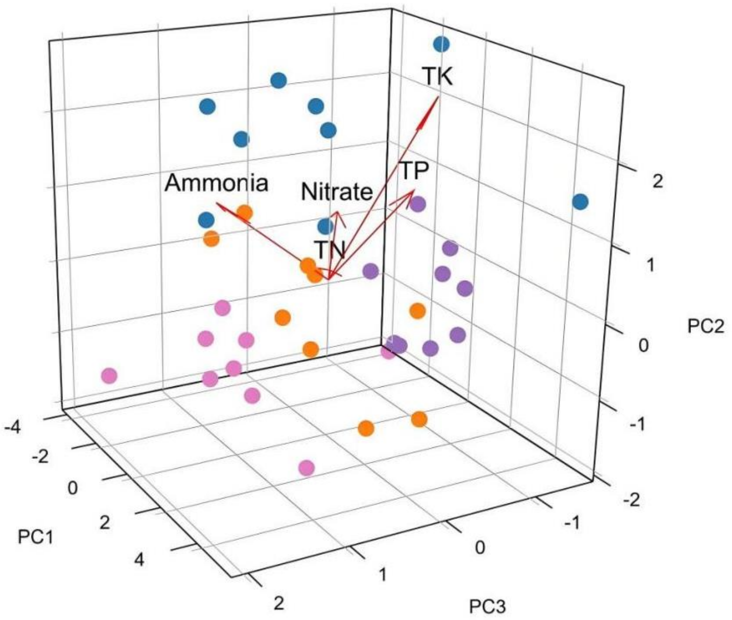

Figure 1. Principle of principal component analysis

Specifically, PCA calculates the covariance matrix of the data and decomposes its eigenvalues, and selects the first few eigenvectors with larger eigenvalues as new axes, and these new axes are known as principal components. In the processing of medical image data, these principal components can be understood as the key features of the image, which can describe the main variations of the data in fewer dimensions. This not only helps to reduce data redundancy, but also improves the efficiency and accuracy of classification algorithms. In addition, PCA is effective in reducing noise and redundant information when processing medical images, thus improving the reliability of diagnosis. By projecting the data into a low-dimensional subspace, PCA enables the system to focus more on those features that have the most impact on the diagnostic results, reducing the computational complexity, which provides more streamlined and effective input data for the machine learning model. This is of great practical significance for the design and realization of medical imaging assisted diagnosis systems.

2.2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a classical machine learning classification technique, its excellent performance in dealing with high-dimensional datasets and complex classification problems, it is widely used in a variety of fields, it has an important role in medical image analysis. The image classification based on SVM is shown in Fig. 2. The core idea of SVM is to separate different categories in a dataset as much as possible by constructing an optimal hyperplane, so as to realize accurate classification. In practice, SVM can not only effectively handle linearly separable data, but also solve linearly indivisible problems by introducing a kernel function to map the data to a higher-dimensional space. This feature enables SVM to show extremely high classification performance when facing complex medical image data [2].

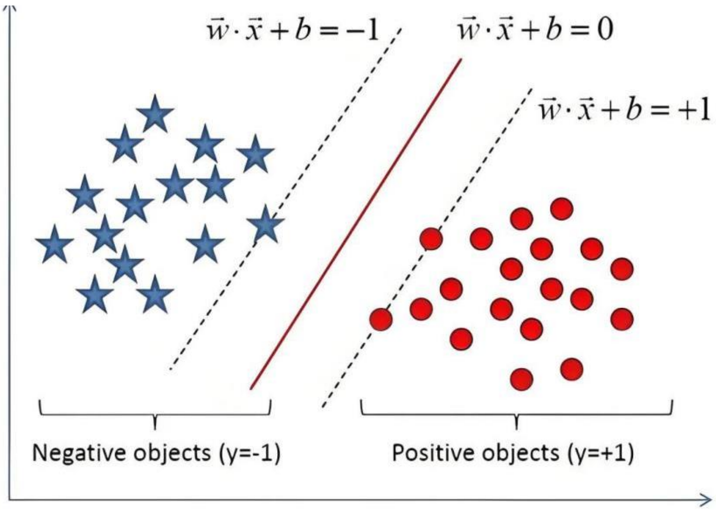

Figure 2. SVM based image classification

The application of SVM in medical image assisted diagnosis system is mainly reflected in the accurate classification of different pathological features. For example, in tumor detection, SVM can accurately distinguish benign and malignant lesions through the analysis of different image features (e.g., texture, shape, edges, etc.), thus providing a reliable basis for clinical diagnosis. Compared with traditional classification methods, SVM has a strong generalization ability and can maintain a high classification accuracy despite small samples and high-dimensional features. This is especially important for the small sample and high dimensionality problems common in medical imaging [3].

Specifically, SVM determines the optimal hyperplane by maximizing the class spacing as a way to ensure the robustness of the classifier when dealing with new data. Assume that there are N training samples$\{(x_1, y_1), (x_2, y_2)..., (x_N, y_N)\}$, where x is a feature vector whose dimension is equal to the number of feature words, and $y\in\{+1, -1\}$ is the sample label. These samples are utilized to train to learn a linear classifier (hyperplane), as shown in equation (1).

$$f(x) = \mathrm{sgn}(w^T x + b) \tag{1}$$

Sgn(x) is the function of taking sign as shown in equation (2).

$$\mathrm{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \tag{2}$$

Assuming training data as shown in equation (3).

$$(x_1, y_1),..., (x_i, y_i), x \in R^m, y \in \{+1, -1\} \tag{3}$$

Assume two hyperplanes as shown in equations. (4), (5).

$$H_1 : w^T x + b = 1 \tag{4}$$

$$H_2 : w^T x + b = -1 \tag{5}$$

Training Objectives.

1) no sample is between these two planes; 2) the distance between these two planes is to be maximized

For the objective l, we can get for any positive example, it has to be on the right side of H1 and for any negative example, it has to be on the left side of H2 as shown in equation (6):

$$y_i (w^T * x_i + b) \geq 1 \tag{6}$$

Formally express the above objective as shown in equation (7).

$$\begin{aligned} &\min \frac{1}{2} \|w\|^2 \\ &s.t. y_i (w^T * x_i + b) \geq 1, \quad \forall x_i \end{aligned} \tag{7}$$

In the design of medical image assisted diagnosis system, SVM is not only used for classification, but also can be combined with other algorithms to further enhance the diagnostic capability of the system. For example, in the processing of multimodal medical data, SVM can be combined with dimensionality reduction techniques such as Principal Component Analysis (PCA) to first reduce the dimensionality of the data and then classify it, thus improving computational efficiency and reducing the impact of noise on the classification results. This multi-algorithm fusion makes SVM show more extensive adaptability and powerful classification ability in practical applications [4].

2.3. Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is a feed-forward neural network with multiple hidden layers, which performs well in nonlinear classification tasks for complex data. The architecture of MLP consists of an input layer, multiple hidden layers, and an output layer, each of which progressively transforms the input data into a feature representation suitable for the classification task by means of a weighted summation and activation function , as shown in Figure 3. In medical image analysis, MLP is widely used to recognize and classify complex medical image data, such as tumor detection, organ segmentation and lesion identification tasks [5]. By introducing a hidden layer, MLP is able to learn the deep-level feature representations in the data to effectively deal with the nonlinear features of high-dimensional data, which enables the model to have higher classification accuracy when facing complex medical images.

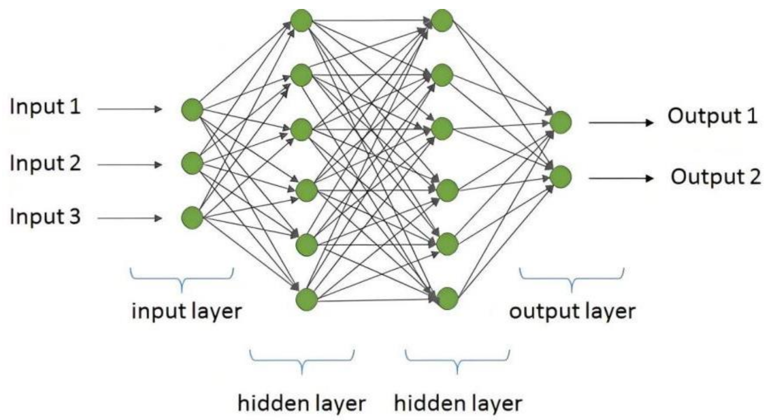

Figure 3. Multi-layer perceptron

The Multi-Layer Perceptron (MLP) optimizes parameters through the Back-Propagation (BP) algorithm, which employs the chain rule to compute the gradient of the loss function with respect to the weights at each layer. By continually adjusting the network weights using gradient descent, this method aims to minimize classification errors. The implementation of the back-propagation algorithm enables the MLP to iteratively refine parameters layer by layer, ensuring that the model captures critical features within medical imaging data for accurate classification. Compared to traditional linear classifiers, the MLP's strength lies in its ability to tackle highly non-linear classification challenges. Through its multi-layered network architecture, the MLP can learn more intricate feature combinations at various levels, a characteristic that proves especially significant in the fine-grained classification of medical images [6].

In practical applications, the performance of the MLP is heavily influenced by the design of the network architecture. The number of hidden layers and the quantity of neurons within each layer directly affect the model’s expressive capacity and computational complexity. To enhance the classification performance of the MLP, meticulous adjustments to the network structure are often necessary, including the selection of appropriate activation functions, optimization algorithms, and regularization techniques to prevent overfitting. In medical imaging-assisted diagnostic systems, the MLP is not only employed for image classification tasks but can also be augmented with other machine learning techniques, such as Principal Component Analysis (PCA) and Support Vector Machines (SVM), to further boost the overall performance of the system. This integration of multiple technologies broadens and enhances the MLP's applicability in the medical field, advancing the development of intelligent diagnostic systems.

3. DESIGN OF MEDICAL IMAGING AUXILIARY DIAGNOSIS SYSTEM BASED ON MACHINE LEARNING

3.1. Intelligent Diagnostic Aid System Architecture Design

The key in the design of the architecture of the intelligent diagnosis assistance system based on machine learning is how to effectively organize and process a large amount of complex medical image data, so as to improve the accuracy and efficiency of diagnosis. The design of the intelligent diagnosis assistance system can be summarized into two main parts: data processing and classification, and the framework of the intelligent diagnosis assistance system is shown in Figure 4. In the data processing section, the system first performs a data preprocessing step, which includes denoising, enhancement and standardization operations on medical image data to ensure the quality and consistency of the input data. Subsequently, the system performs vectorized representation of features, which aims to transform complex image information into numerical features that can be processed by machine learning algorithms. This step is often combined with feature extraction techniques such as Convolutional Neural Networks (CNNs) to extract edge, texture, and shape features of the image, or dimensionality reduction using Principal Component Analysis (PCA) to reduce the dimensionality of the data while retaining key information [7].

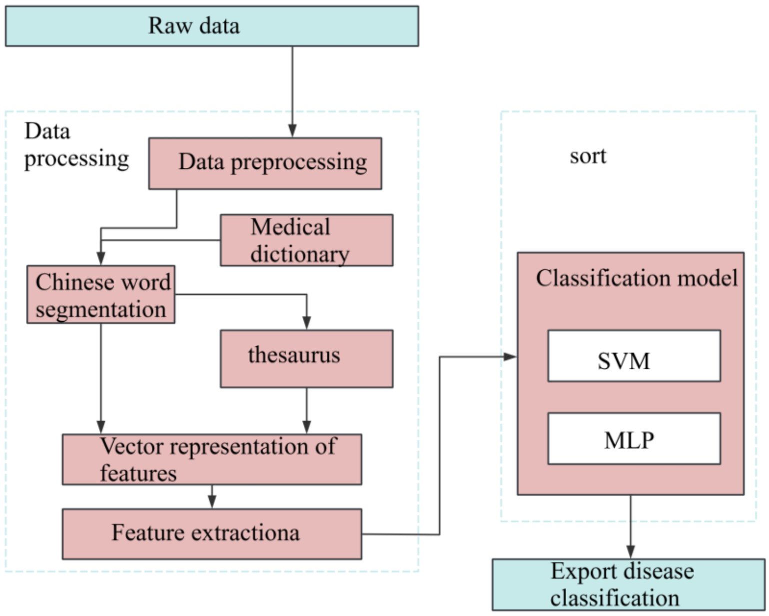

Figure 4. Intelligent Diagnostic Aids Framework

In the classification phase, the intelligent diagnostic assistance system employs a variety of machine learning algorithms for data categorization. Among these, Support Vector Machines (SVM) serve as a prevalent classification technique by identifying the optimal hyperplane to separate data into distinct categories, accommodating both linear and nonlinear data. SVM is particularly effective in handling high-dimensional data with small sample sizes, making it ideal for tasks such as tumor detection and lesion area identification. Additionally, the Multilayer Perceptron (MLP), a deep learning model, offers enhanced nonlinear classification capabilities suitable for complex multi-class problems. Through its multi-layered neural network architecture, MLP progressively extracts and learns intricate features from the data, achieving high classification accuracy when dealing with complex medical imaging data.

The architectural design of the intelligent diagnostic assistance system must not only ensure accuracy in data processing and classification but also focus on the system's scalability and robustness. To guarantee adaptability across various application scenarios, modular design is typically employed, allowing for independent development and updating of individual functional modules. Moreover, the system design must also take into account hardware resource limitations and algorithmic computational complexity, optimizing algorithms and data structures to enhance operational efficiency and stability. By integrating advanced machine learning algorithms and data processing techniques, the intelligent diagnostic assistance system provides an efficient and precise solution for medical imaging analysis, facilitating the formulation of clinical diagnoses and treatment plans [8].

3.2. Data Processing in Intelligent Assisted Diagnostic Systems

Data preprocessing in intelligent diagnostic systems is a pivotal step in the overall design, profoundly impacting the performance and accuracy of subsequent classification models. In the realm of medical imaging and textual data processing, data preprocessing primarily encompasses data cleansing, feature extraction, and vectorization. During the data cleansing phase, the system eliminates noise, redundant information, and other irrelevant elements to ensure the efficacy of subsequent processing. For instance, when handling medical records, the cleansing process may involve removing stop words, Western characters, and other extraneous content. This process significantly enhances data quality, enabling the model to more accurately identify and extract useful information.

Subsequently, the Jieba segmentation tool is employed to tokenize the cleansed text, breaking it down into a series of feature words. After statistical analysis, words with higher frequencies are selected as candidate words and further refined through manual selection to establish the final feature word library. The construction of this feature word library is crucial for enhancing classification accuracy, as it directly influences the quality and expressive power of the model's input feature vectors.

The final step in data preprocessing involves the construction of feature vectors. By matching the original medical record text with the feature word library, the system generates feature vectors for classifier input. The matching process may employ exact or fuzzy matching, adhering to specific rules, such as the propagation of negation, to ensure that the generated feature vectors accurately reflect the semantic information of the text. Ultimately, these feature vectors are input into classifiers, such as Support Vector Machines (SVM), Multi-Layer Perceptrons (MLP), and Long Short-Term Memory networks (LSTM), for the classification and analysis of medical record texts.

4. SYSTEM PERFORMANCE EVALUATION EXPERIMENT

The system performance evaluation experiment is crucial in the design of intelligent assisted diagnosis systems, aiming to verify the performance of various types of machine learning models in medical image analysis tasks to ensure that the system can achieve the expected accuracy and stability in practical applications. This experiment evaluates different models such as Support Vector Machine (SVM), Multilayer Perceptual Machine (MLP) and Long Short-Term Memory Network (LSTM) in detail to determine the optimal model and its application scenarios.

Support Vector Machine (SVM) is a common classifier that is especially suitable for dealing with small samples of high-dimensional data. In this experiment, SVM showed better linear classification ability. In designing SVM applied to COPD classification, we randomly selected 1000 cases out of 1200 cases as training set and the remaining 200 cases as test set. In negative sample, 2000 cases were used as training set and 300 cases as test set. The test results were obtained as shown in Table 1.

Table 1. Experimental results of chronic obstructive pulmonary disease (COPD)

Category of disease	Whether to use fuzzy matching	Whether to use fuzzy matching	Recall rate	Recall rate
Chronic obstruction	Y	is	0.9100	0.9100
Pulmonary disease	N	no	0.9450	0.9450

Multilayer Perceptron (MLP) demonstrates its advantages in nonlinear problems in this experiment. As a deep learning model, MLP extracts deep features from data layer by layer through a multilayer neural network structure. In the medical image classification task, the correctness curve of MLP gradually increases with the number of iterations, and finally converges to the ideal classification accuracy. The final output layer classification function is set as softmax function and training is done by stochastic gradient descent (SGD) method. Since the softmax function has only 0 and 1 outputs, we set the output unit to have two, and encode the three types of diseases with two 0/1 bits. Where diabetes is coded 00, cerebral infarction is coded 01, and COPD is coded 10. The experimental results obtained are shown in Table 2.

Table 2. Results of experiments on the use of MLP classification for various types of diseases

Category of disease	Whether to use fuzzy matching	Accuracy rate	Recall rate	F1
diabetes	Y	0.9161	0.9467	0.9311
	N	0.9000	0.9600	0.9290
Cerebral infarction	Y	0.9130	0.9450	0.9287
	N	0.8981	0.9700	0.9327
Chronic obstructive pulmonary disease	Y	0.8414	0.9550	0.8946
	N	0.8262	0.9750	0.8945

Long Short-Term Memory Networks (LSTMs) have significant advantages in processing time-series data, but in this still-image categorization task, the performance of LSTMs is mainly characterized by their nonlinear ability in dealing with complex multi-class classification tasks. We also utilized the LSTM method, which is currently popular for neural networks, to experiment with this problem. The model building part directly references the text classification LSTM samples of Keras platform [9]. The training set and test set division are unchanged from the above, and the experimental results we obtained are shown in Table 3.

Table 3. Experimental results of classification using LSTM for various diseases

Category of disease	Whether to use fuzzy matching	Accuracy rate	Recall rate	F1
diabetes	Y	0.8296	0.3733	0.5149
	N	0.7500	0.3500	0.4773
Cerebral infarction	Y	0.7672	0.4450	0.5633
	N	0.8987	0.7100	0.7933
Chronic obstructive pulmonary disease	Y	0.6768	0.6700	0.6734
	N	0.7488	0.7600	0.7543

The experimental results indicate that the three models each have distinct advantages across various application scenarios. The SVM is well-suited for linear and small-sample binary classification tasks; the MLP excels in handling multi-class classification problems, particularly for complex and moderately nonlinear medical imaging data; and the LSTM demonstrates superior performance in capturing temporal sequence information or addressing intricate nonlinear relationships. By comprehensively evaluating these models, the intelligent diagnostic assistance system can select the optimal model for different clinical applications, thereby achieving more efficient and accurate medical diagnostic support. This rigorous performance assessment provides a solid theoretical foundation and technical support for the system’s practical deployment, ensuring it can realize its full potential in real-world applications [10].

5. CONCLUSION

This study explores the application of machine learning techniques in medical imaging-assisted diagnosis, proposing and implementing an intelligent diagnostic system based on Principal Component Analysis, Support Vector Machines, and Multilayer Perceptrons. The system demonstrates high classification accuracy and stability in handling complex medical imaging data, providing substantial support to clinicians by reducing human error and enhancing diagnostic efficiency. Experimental results validate the system's potential in practical applications and offer crucial references for further optimization and expansion. Despite the significant progress achieved, challenges such as data diversity, algorithm optimization, and system integration persist in real-world deployment. Future work will focus on addressing these aspects to facilitate broader clinical applications. The findings of this study not only provide new directions for the development of medical imaging-assisted diagnostic systems but also lay a solid theoretical and practical foundation for the design of machine learning-based medical tools.

REFERENCES

[1] Cheng G, He L. Dr. Pecker: A Deep Learning-Based Computer-Aided Diagnosis System in Medical Imaging [J]. Deep Learning in Healthcare: Paradigms and Applications, 2020: 203-216.

[2] Giger M L. Machine learning in medical imaging [J]. Journal of the American College of Radiology, 2018, 15(3): 512-520.

[3] Zhou Z, Qian X, Hu J, et al. An artificial intelligence-assisted diagnosis modeling software (AIMS) platform based on medical images and machine learning: a development and validation study [J]. Quantitative Imaging in Medicine and Surgery, 2023, 13(11): 7504.

[4] Ghosh S, Das S, Mallipeddi R. A deep learning framework integrating the spectral and spatial features for image-assisted medical diagnostics [J]. Ieee Access, 2021, 9: 163686-163696.

[5] Kumar A, Bi L, Kim J, et al. Machine learning in medical imaging[M]//Biomedical Information Technology. Academic Press, 2020: 167-196.

[6] Rehouma R, Buchert M, Chen Y P P. Machine learning for medical imaging-based COVID-19 detection and diagnosis [J]. International Journal of Intelligent Systems, 2021, 36(9): 5085-5115.

[7] Tian J, Li H, Qi Y, et al. Intelligent Medical Detection and Diagnosis Assisted by Deep Learning [J]. Applied and Computational Engineering, 2024, 64: 121-126.

[8] Oza P, Sharma P, Patel S. Machine learning applications for computer-aided medical diagnostics[C]//Proceedings of Second International Conference on Computing, Communications, and Cyber-Security: IC4S 2020. Springer Singapore, 2021: 377-392.

[9] Jeyaraj P R, Samuel Nadar E R. Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm [J]. Journal of cancer research and clinical oncology, 2019, 145: 829-837.

[10] Guetari R, Ayari H, Sakly H. Computer-aided diagnosis systems: a comparative study of classical machine learning versus deep learning-based approaches [J]. Knowledge and Information Systems, 2023, 65(10): 3881-3921.