Progress in Diagnosis and Prediction of Common Cancers: Multi-Cancer Characteristics, Technical Applications, and AI Model Practices

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Abstract. Cancer remains a major global health burden, and its early diagnosis and accurate prediction are crucial for improving patient prognosis. This paper reviews three common types of cancers—gastric cancer, skin cancer, and brain tumors—focusing on their pathological mechanisms, pathogenic factors, clinical manifestations, and diagnostic technologies, while emphasizing the application progress of artificial intelligence (AI) models in cancer diagnosis. Research shows that Helicobacter pylori (H. pylori) infection is a core pathogenic factor for gastric cancer, and endoscopy combined with narrow-band imaging technology can significantly improve the accuracy of early diagnosis. Among skin cancers, melanoma has the highest malignancy, and dermoscopy combined with pathological biopsy is the mainstream diagnostic method; AI models in identifying skin cancer images have achieved high accuracy. Gliomas are the most common type of brain tumors, and magnetic resonance imaging combined with gene detection can improve the accuracy of grading; AI models can achieve rapid localization of tumor regions. Current cancer diagnosis still faces challenges such as insufficient sample size, the "black box" issue of AI models, and difficulties in clinical translation. In the future, it is necessary to promote technological implementation by building multi-center databases, developing explainable AI, and strengthening industry-academia-research cooperation.

Keywords: Cancer Diagnosis; Artificial Intelligence; Gastric Cancer; Skin Cancer; Brain tumors.

1 Introduction

According to GLOBOCAN 2020 data, there are over 19.3 million new cancer cases and nearly 10 million cancer-related deaths worldwide each year [1]. Among these, gastric cancer, skin cancer, and brain tumors account for 5.6%, 4.2%, and 1.6% of new cancers, respectively, with significant differences in prognosis—the 5-year survival rate of gastric cancer is less than 30%, that of early-stage melanoma reaches 99%, and that of glioblastoma is only 6.8% [1, 2]. Traditional cancer diagnosis relies on pathological sections, imaging examinations, and a doctor's experience, which suffers from high early missed diagnosis rates. For example, gastric cancer has no symptoms in the early stage, and 70% of cases in developed Western countries are diagnosed at an advanced

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stage [3]. It also faces difficulties in subtype identification as there are more than 150 subtypes of brain tumors [4], and the poor generalization ability of prediction models.

With the development of molecular biology and artificial intelligence (AI) technology, cancer diagnosis has shifted from "experience-driven" to "technology-driven". H. pylori eradication can reduce the risk of gastric cancer by 46% [1], the accuracy of AI models in skin cancer identification exceeds that of junior clinicians [5], and multi-modal image fusion technology can improve the accuracy of brain tumor grading [2]. From three dimensions—pathological and clinical characteristics of multi-cancers, analysis of subdivided brain tumor types, and application of AI model technologies—this paper systematically summarizes current research results and provides directions for optimizing cancer diagnosis and prediction technologies.

2 Diagnosis and Prediction of Common Cancers (Classified by Cancer Type)

2.1 Diagnosis and Prediction of Gastric Cancer

Gastric cancer is highly prevalent in East Asia, Eastern Europe, and South America, with China, Japan, and South Korea accounting for over 60% of the global incidence[1]. Its pathogenic mechanism is closely related to the "Correa cascade", which progresses from chronic non-atrophic gastritis to atrophic gastritis, then to intestinal metaplasia, dysplasia, and finally adenocarcinoma[6].

Core Pathology and Etiology. Pathological factors show that Helicobacter pylori (H. pylori) is a Class I carcinogen defined by the World Health Organization (WHO), and 74.7% of non-cardia gastric cancers worldwide are associated with this infection[3]. The Eurogast-EPIC study showed that the positive rate of H. pylori in gastric cancer patients in Europe reached 93.2%, while only 0.66% of gastric cancer patients in Japan had no signs of H. pylori infection[3]. In addition, atrophic gastritis (especially atrophy of the gastric body) can increase the risk of gastric cancer by 8 times, and the annual probability of intestinal metaplasia progressing to cancer is 0.2%-1.8%[6].

Pathogenic factors include a high-salt diet, processed meat consumption, smoking, genetic factors, and protective factors such as the intake of fresh vegetables and long-term use of aspirin. A daily sodium intake exceeding 3960 mg can increase the risk of non-cardia gastric cancer by 2.26 times[1]. A daily increase of 50 g in processed meat consumption can increase the risk by 1.34 times[1]. The risk of current smokers is 1.6 times higher than that of non-smokers[1]. The risk of first-degree relatives of cancer patients is increased by 3 times[6]. Intake of 100 g of fresh vegetables per day can reduce the risk by 15%[1], and long-term use of aspirin can reduce the risk of non-cardia gastric cancer by 30%[1].

Clinical Manifestations and Diagnostic Technologies. Clinical manifestations of early gastric cancer have no specific symptoms, and only 10%-15% of patients

experience mild stomach pain and acid regurgitation. Advanced-stage manifestations include hematemesis with an incidence rate of 30%, significant weight loss with over 10% weight loss in 6 months, and obstructive vomiting[3]. Due to the implementation of endoscopic screening in Japan, the early diagnosis rate of gastric cancer reaches 70%, with a 5-year survival rate of 95%, while the early diagnosis rate in developed Western countries is less than 20%[3].

Diagnostic methods show that endoscopic biopsy is the gold standard. Narrow-band imaging (NBI) combined with magnifying endoscopy (ME) can observe mucosal microvessels and surface structures, which significantly improves the accuracy of early gastric cancer diagnosis compared with white-light endoscopy[3]. Serum pepsinogen (Pg) detection with a Pg I/II ratio < 3.0 has a sensitivity of 77% for atrophic gastritis and can be used as a primary screening tool for high-risk groups, but its sensitivity for gastric cancer is relatively low, leading to frequent missed diagnoses[3].

Literature-Supported Cases. Pasechnikov et al. found in a multi-center study in East Asia and Europe that the reversal rate of gastric body atrophy reached 53% after H. pylori eradication, but antral atrophy was irreversible [3]. A randomized controlled trial by Fukase et al. showed that after endoscopic resection of early gastric cancer, the incidence of metachronous gastric cancer decreased from 24% to 9% in patients with H. pylori eradication [7]. Based on data from 185 countries, Thrift et al. predicted that the number of global gastric cancer cases will reach 1.77 million by 2040, and implementing H. pylori screening and eradication strategies in high-risk areas can reduce new cases by 25% [1].

2.2 Diagnosis and Prediction of Skin Cancer

Skin cancer is mainly divided into melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). Among them, melanoma has the highest malignancy, accounting for 75% of skin cancer deaths [5], and is more common in regions with strong ultraviolet exposure such as Australia and South Africa.

Core Pathology and Etiology. Pathological factors indicate that melanoma originates from abnormal proliferation of melanocytes. According to the Breslow thickness classification, with ≤ 1 mm for the early stage and > 4 mm for the advanced stage, the 5-year survival rate decreases by 15% for each 1 mm increase in thickness [8]. BCC originates from basal cells of the epidermis, mostly showing local invasion with a metastasis rate of < 0.1%. SCC originates from squamous epithelial cells with a metastasis rate of approximately 2%-5% [5].

Pathogenic factors include ultraviolet B (UVB) exposure as the primary factor, followed by genetic factors, immunodeficiency, and chemical carcinogens. The risk of long-term UVB exposure is increased by 3 times [8]. The lifetime risk of CDKN2A gene mutation carriers reaches 60% [5]. The risk of HIV-infected patients is increased by 5 times [8]. Arsenic exposure is one of the chemical carcinogens.

Clinical Manifestations and Diagnostic Technologies. Clinical manifestations show that the typical characteristics of melanoma conform to the "ABCDE principle," including Asymmetry, Border irregularity, Color variegation, Diameter > 6 mm, and evolving. BCC often presents as "pearl-like nodules" with telangiectasia. SCC mostly appears as ulcerative masses, prone to bleeding [5].

Diagnostic methods show that dermoscopy is the preferred primary screening tool, with a high sensitivity and specificity for melanoma [8]. Pathological biopsy is the basis for confirmation, and immunohistochemistry such as S-100 and HMB-45 staining, can identify subtypes. Among AI models, attention-based convolutional neural networks (CNN) combining object-level and part-level focus have higher accuracy in identifying skin cancer images than traditional CNN [5].

2.3 Diagnosis and Prediction of Brain Tumors

Among brain tumors, gliomas account for 45%, pituitary adenomas for 15%, and meningiomas for 20%[4]. Their diagnosis relies on the combination of imaging and molecular detection. The 2021 WHO Classification of Tumours of the Central Nervous System has incorporated molecular indicators such as isocitrate dehydrogenase 1 (IDH1) mutation and 1p/19q codeletion into the grading criteria [2].

Core Pathology and Etiology. Pathological factors show that glioblastoma (GBM, Grade IV glioma) is characterized by "pseudopalisading necrosis" and "microvascular proliferation". The median survival time of patients with IDH1 mutation is significantly longer than that of wild-type patients [2]. Prolactinomas account for 40% of pituitary adenomas, mostly benign, and only 3% progress to invasiveness [9]. Meningiomas originate from arachnoid granule cells, with WHO Grade I accounting for 80% and a recurrence rate of < 5% [4].

Pathogenic factors include high-dose radiation, Epstein-Barr virus (EBV) infection, and genetic syndromes. The risk of patients with a head and neck radiotherapy history is increased by 7 times [2]. EBV infection is associated with central nervous system lymphoma [4]. The risk of glioma in patients with neurofibromatosis type 1 is increased by 200 times [9]. There is no clear evidence for the association between environmental factors such as mobile phone radiation and brain tumors.

Clinical Manifestations and Diagnostic Technologies. Clinical manifestations show that most GBM patients present with headache with an incidence rate of 70%, epilepsy with 30%, and limb weakness with 25% [2, 4]. Pituitary adenomas often cause amenorrhea and galactorrhea in prolactinomas or acromegaly in growth hormone-secreting adenomas due to hormonal abnormalities [9]. Most meningiomas are incidentally discovered, and only 20% cause vision loss due to compression of brain tissue [4, 9].

Diagnostic methods show that magnetic resonance imaging (MRI) is the core imaging method. Contrast-enhanced MRI can clearly show tumor blood supply, with GBM showing "ring enhancement" and meningiomas showing "homogeneous enhancement"[2]. In molecular detection, IDH1/2 mutation and MGMT promoter

methylation can guide treatment selection, and patients with MGMT methylation have a higher response rate to temozolomide chemotherapy[2].

3 Diagnosis and Prediction of Subdivided Brain Tumor Types

Accurate identification of brain tumor subtypes is a prerequisite for formulating treatment plans. The prognosis of different subtypes varies significantly. For example, the 5-year survival rate of WHO Grade I glioma is > 90%, while that of Grade IV is only 6.8% [2]. It requires a comprehensive judgment based on pathology, imaging, and molecular characteristics.

3.1 Diagnosis and Prediction of Brain Gliomas

Gliomas are the most common malignant tumors of the central nervous system, classified into Grades I-IV according to the WHO. Among them, Grade I such as pilocytic astrocytoma is benign, and Grade IV (GBM) is highly malignant [2].

Pathological and molecular characteristics show that low-grade gliomas (LGG, Grade II) are characterized by "diffuse growth", with an IDH mutation rate of 70%-80%. Patients with 1p/19q codeletion are mostly oligodendrogliomas with a better prognosis with a median survival time of 10 years. In GBM, the EGFR amplification rate reaches 50% and the PTEN mutation rate is 30%, and these mutations are closely related to tumor invasiveness [2].

Diagnostic technologies show that multi-modal MRI including T1 contrast-enhanced, T2-FLAIR, and DWI can distinguish tumor parenchyma from edematous areas. Perfusion MRI (PWI) shows that the relative cerebral blood volume (rCBV) of GBM is 3-5 times that of normal brain tissue. In AI models, 3D CNN combined with multi-sequence MRI features has high accuracy in distinguishing LGG from GBM and identifying IDH-mutant and wild-type gliomas [2].

3.2 Diagnosis and Prediction of Pituitary Adenomas

Most pituitary adenomas are benign, divided into microadenomas with diameter < 10 mm and macroadenomas with diameter > 10 mm. Functional adenomas such as prolactinomas and growth hormone-secreting adenomas account for 60% [9].

Pathological and hormonal characteristics show that prolactinomas are positive for prolactin (PRL) in immunohistochemistry, and growth hormone-secreting adenomas are positive for growth hormone (GH). Non-functional adenomas have no hormonal abnormalities, but macroadenomas can compress the optic chiasm, leading to bitemporal hemianopia [9].

Diagnostic technologies show that MRI with thin-section contrast-enhanced pituitary scan can detect microadenomas with a diameter > 2 mm. The serum PRL level of patients with prolactinomas is often > 200 ng/mL, while the normal level is < 25 ng/mL. In AI models, the localization accuracy of YOLOv5 for pituitary adenomas reaches 96%, which can assist in judging whether the tumor invades the cavernous sinus[9].

3.3 Diagnosis and Prediction of Meningiomas

Most meningiomas originate from arachnoid granules, with WHO Grade I accounting for 80%, and the recurrence rates of Grade II (atypical) and Grade III (anaplastic) are 25%-40% and 50%-70%, respectively [4].

Pathological and imaging characteristics show that Grade I meningiomas show "psammomatous calcification" and are positive for EMA and vimentin in immunohistochemistry. Grade II meningiomas have > 4 mitoses per 10 HPF. MRI T2WI shows that most Grade I meningiomas are isointense, while Grade II meningiomas are mostly hyperintense [4].

Diagnostic technologies show that computed tomography (CT) can detect calcification with a sensitivity of 80%. MRI T2WI shows that most Grade I meningiomas are isointense and Grade II are mostly hyperintense. In AI models, the Transformer combined with MRI features has an accuracy of 88% in grading meningiomas [2].

4 Cancer Diagnosis and Prediction Based on AI Models

By extracting deep features from image, pathological, and molecular data, AI models solve problems such as subjective bias, low efficiency, and poor generalization in traditional diagnosis. Among them, CNN is good at feature extraction, and You Only Look Once (YOLO) is good at object localization, both of which have mature applications in multi-cancer diagnosis.

4.1 Methods Based on CNN Models

CNN extracts local features through convolutional layers and pooling layers, and performs well in cancer image recognition, especially suitable for the analysis of endoscopic images, pathological sections, and dermoscopic images.

In gastric cancer diagnosis, CNN combined with NBI images (focusing on the disappearance of mucosal structure, microvascular dilation, and heterogeneity) has higher sensitivity and specificity for early gastric cancer than white-light endoscopy [3]. The CNN model developed by Machlowska et al. has high accuracy in identifying intestinal metaplasia in gastric cancer pathological sections, which can replace manual slide reading [6].

In skin cancer diagnosis, AI models with attention mechanisms first locate skin lesion areas (object-level attention) and then focus on key features such as pigment and borders (part-level attention), achieving accuracy in melanoma recognition that surpasses junior clinicians [5]. The few-shot CNN model by Dhillon et al. achieves a certain accuracy in skin cancer recognition with only 5 labeled images, solving the problem of scarce samples [10].

In brain tumor diagnosis, 3D CNN models fusing T1, T2, and FLAIR sequence features of MRI have high accuracy in distinguishing LGG from GBM and identifying IDH-mutant and wild-type gliomas [2]. The Dice coefficient (tumor region matching degree) of these models on the BraTS 2020 dataset is higher than that of traditional radiomics methods [2].

4.2 Methods Based on YOLO Models

YOLO is a real-time object detection model that realizes rapid localization through grid division, bounding box prediction, and category judgment, and is suitable for scenarios requiring clear lesion localization such as brain tumors and gastric cancer.

In brain tumor localization, the detection speed of YOLOv5 in brain tumor MRI images is faster than Faster R-CNN, with a small bounding box localization error for glioblastoma [2]. In few-shot scenarios with 10 labeled images, YOLOv7 combined with transfer learning achieves high localization accuracy for pituitary adenomas, which can assist in endoscopic surgical planning [9].

In gastric cancer lesion detection, by transferring the idea of industrial defect detection to gastric cancer diagnosis, the detection rate of YOLOv8 for "flat lesions" prone to missed diagnosis in endoscopic images is higher than manual slide reading [3]. The false positive rate of this model on the Japanese gastric cancer screening dataset is low, suitable for large-scale population screening.

The advantage of YOLO lies in real-time performance, which can meet the needs of real-time navigation in clinical surgery. However, its sensitivity to small lesions such as brain metastases < 5 mm is relatively low, which needs further optimization combined with high-resolution images [2].

5 Current Limitations and Future Prospects

5.1 Core Limitations

Data level limitations include insufficient sample size for some cancer types leading to poor generalization ability of AI models. The global sample size of pancreatic cancer is only 1/10 of that of gastric cancer, and the model accuracy varies in different populations [1]. Inconsistent multi-center data annotation standards affect model training. For example, the consistency of OLGA/OLGIM staging for gastric cancer atrophy among different centers is only 70% [3].

Technical level limitations show that the "black box" problem of AI models is prominent. AI models have high accuracy in skin cancer recognition but cannot explain the judgment basis [5]. Multi-modal data fusion is difficult. Current models only integrate 2 modalities, failing to make full use of multi-dimensional information [2].

Clinical translation limitations indicate that 80% of AI models remain in the laboratory stage, and only 2% enter clinical verification. The reasons include the lack of prospective trials such as whether AI-assisted diagnosis reduces the missed diagnosis rate and restrictions of medical regulations such as the long FDA approval cycle for AI diagnostic equipment[10].

5.2 Future Directions

Data construction efforts include building multi-center shared databases. For example, the European Union’s "Cancer Imaging Archive" has integrated gastric cancer and brain tumor imaging data from 15 countries with a large sample size[4]. Establishing annotation standard systems such as the "Cancer Image Annotation Guidelines"

launched by the WHO to unify the definition of lesions in brain tumors and skin cancer[4].

Technological innovation involves developing explainable AI (XAI). For example, displaying pathological regions focused on by AI models through "attention heatmaps" such as "asymmetric borders" of melanoma to improve clinical trust [5]. Fusing multi-modal data such as the "MRI + gene + pathology" Transformer model, which has a certain accuracy in prognostic prediction of glioblastoma [2].

Clinical implementation requires promoting "industry-academia-research" cooperation. For example, the prospective trial of AI-assisted skin cancer diagnosis conducted by medical institutions involves a large number of patients [8]. Developing portable devices such as AI dermoscopes with low cost, suitable for screening needs in low-income regions[8].

6 Conclusion

This paper systematically summarizes the research progress in the diagnosis and prediction of gastric cancer, skin cancer, and brain tumors. It is found that H. pylori eradication, dermoscopy screening, and MRI molecular imaging remain the core clinical technologies currently, while AI models (CNN, YOLO) show significant advantages in improving accuracy, enhancing efficiency, and solving few-shot problems. AI models' accuracy in skin cancer recognition surpasses that of junior doctors, and YOLO realizes real-time localization of brain tumors, providing new tools for precise cancer diagnosis.

Current research still needs to overcome three major obstacles: data bottleneck, technical black box, and clinical translation. In the future, through multi-center data sharing, the development of explainable AI, and in-depth industry-academia-research cooperation, it is expected to realize the whole-process optimization of early diagnosis, precise typing, and prognostic prediction, ultimately reducing cancer mortality and promoting the development of precision medicine.

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