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(57) Abstract:

The present invention discloses a deep learning-based predictive system for cancer detection and classification using multi-modal biomedical data integrated with temporal feature fusion mechanisms. The system acquires heterogeneous medical datasets including medical images, genomic profiles, laboratory reports, and electronic health records. Advanced deep learning architectures are employed for automatic feature extraction and temporal disease progression analysis. An adaptive feature fusion mechanism integrates spatial and sequential biomedical representations to improve diagnostic accuracy and predictive reliability. The proposed framework supports early-stage cancer detection, tumor classification, progression monitoring, and personalized healthcare decision-making. The invention provides enhanced scalability, reduced diagnostic complexity, and improved performance suitable for real-time healthcare and intelligent clinical environments.

FORM 2

THE PATENT ACT, 1970

(39 F 1970)

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The Patents Rules, 2003

PROVISIONAL/COMPLETE SPECIFICATION

(See section 10, rule 13)

A Deep Learning-Based Predictive System for Cancer Detection and Classification Using Multi-Modal Biomedical Data and Temporal Feature Fusion

Background of the Invention

1. Cancer remains one of the leading causes of mortality worldwide and early diagnosis plays a critical role in improving patient survival rates and treatment outcomes. Conventional cancer diagnosis methods rely heavily on manual examination of medical images, laboratory reports, and biopsy analysis, which are often time-consuming and prone to human error. The increasing complexity of biomedical data has created significant challenges for healthcare professionals in making accurate and timely clinical decisions. As the volume of patient data continues to grow, automated intelligent systems are becoming essential for effective cancer diagnosis. Therefore, advanced computational models capable of handling complex medical datasets are urgently required.
2. Traditional machine learning approaches used for cancer detection often depend on handcrafted feature extraction methods that require expert intervention and domain-specific knowledge. These approaches may fail to capture hidden nonlinear relationships among various biomedical attributes and may produce inconsistent diagnostic performance across diverse datasets. In addition, single-modality diagnostic systems are limited in their ability to provide comprehensive insights into cancer progression. The lack of integration among imaging, genomic, and clinical information restricts the predictive capability of conventional diagnostic frameworks. Consequently, there is a

need for advanced multi-modal learning systems that can effectively combine heterogeneous medical information.

3. Recent advancements in deep learning have demonstrated promising results in medical image analysis and disease prediction applications. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based architectures have shown improved capability in extracting meaningful features from biomedical data. However, many existing systems primarily focus on static image analysis and fail to incorporate temporal disease progression patterns into the diagnostic process. Temporal variations in patient health records and sequential medical observations contain valuable information regarding cancer development and metastasis. Ignoring such temporal dependencies may reduce the reliability and robustness of prediction models.
4. The integration of multi-modal biomedical data poses additional technical challenges related to feature heterogeneity, data dimensionality, synchronization, and computational complexity. Medical datasets obtained from different diagnostic modalities often vary in scale, resolution, and representation format. Existing diagnostic frameworks struggle to efficiently fuse temporal and spatial information while maintaining high predictive accuracy and computational efficiency. Moreover, the absence of adaptive feature fusion mechanisms limits the capability of existing systems to dynamically prioritize clinically relevant information. Therefore, there exists a need for an intelligent temporal feature fusion framework capable of learning meaningful representations from diverse biomedical data sources.
5. Furthermore, healthcare institutions require scalable and automated diagnostic systems that support early-stage cancer screening and classification with minimal human intervention. The growing adoption of precision medicine and personalized healthcare has increased demand for predictive systems capable of delivering accurate risk assessment and subtype classification. Current diagnostic technologies often suffer from delayed prediction, limited scalability, and reduced generalizability across different cancer types. Hence, the development of a robust deep learning-based predictive system integrating multi-modal biomedical data and temporal feature fusion can significantly improve clinical decision-making and cancer diagnosis efficiency.

Field of the Invention

The present invention generally relates to the fields of artificial intelligence, biomedical informatics, medical imaging, and healthcare analytics. More particularly, the invention relates to a deep learning-based predictive framework for early cancer detection and classification using multi-modal biomedical datasets integrated with temporal feature fusion mechanisms. The invention further relates to automated diagnostic systems capable of analyzing heterogeneous medical data such as radiological images, histopathological scans, genomic information, clinical records, and temporal patient progression data for enhanced cancer diagnosis and classification accuracy.

Background Technology of the Invention

6. Existing computer-aided diagnostic systems primarily utilize image processing and traditional machine learning techniques for detecting abnormalities in medical scans. Techniques such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors are widely used for cancer classification tasks. However, these methods depend heavily on manual feature engineering processes and often fail to generalize effectively on large-scale heterogeneous datasets. Their predictive performance is also affected by noise, missing values, and variations in imaging protocols. Such limitations reduce the clinical applicability of traditional diagnostic frameworks.
7. Deep learning technologies have recently transformed the field of medical diagnostics through automatic feature extraction and representation learning. Convolutional Neural Networks have been successfully applied to detect tumors from MRI, CT, PET, and histopathological images with high accuracy. Similarly, recurrent architectures such as Long Short-Term Memory (LSTM) networks are capable of analyzing sequential medical records and temporal patient information. Despite these advancements, most existing frameworks focus only on a single type of biomedical data source. The lack of comprehensive multi-modal integration limits diagnostic precision and interpretability.
8. Several research works have proposed multi-modal learning systems combining imaging data with electronic health records or genomic information. These systems generally utilize feature concatenation or ensemble learning methods for data fusion. However, simple fusion strategies may not effectively capture interdependencies between

heterogeneous biomedical modalities. In many cases, the fused features may contain redundant or irrelevant information that negatively affects classification accuracy. Furthermore, static fusion mechanisms lack adaptability to varying patient conditions and disease progression patterns.

9. Temporal feature analysis has gained significant attention in healthcare analytics due to its capability to model disease evolution over time. Sequential deep learning models such as gated recurrent units and temporal transformers are increasingly used to monitor patient health progression. Nevertheless, current systems often process temporal information independently without integrating it effectively with spatial and multi-modal features. This separation limits the ability of predictive models to identify complex correlations among temporal biomarkers and imaging characteristics. Efficient temporal-spatial fusion remains a major challenge in biomedical predictive analytics.
10. Modern healthcare environments require intelligent and scalable systems capable of supporting real-time cancer diagnosis and personalized treatment planning. Cloud-based healthcare infrastructures and Internet of Medical Things (IoMT) devices generate large volumes of biomedical data continuously. Existing systems are not fully optimized to process and analyze such large-scale temporal and multi-modal datasets efficiently. Additionally, issues related to computational overhead, model interpretability, and data integration complexity continue to hinder practical deployment. Therefore, there is a need for an improved deep learning-based predictive framework capable of addressing these technological limitations.

Summary of the Invention

The present invention discloses a deep learning-based predictive system for cancer detection and classification using multi-modal biomedical data integrated with temporal feature fusion techniques. The proposed system is designed to process heterogeneous medical datasets including radiological images, histopathological images, genomic profiles, laboratory records, and electronic health records. The invention utilizes advanced deep neural architectures for automatic feature extraction and representation learning from diverse biomedical modalities.

The invention introduces a temporal feature fusion mechanism that combines spatial, sequential, and contextual biomedical information to improve predictive performance and diagnostic reliability. The framework employs convolutional neural networks for extracting spatial imaging features and recurrent or transformer-based networks for learning temporal dependencies from sequential patient data. An adaptive fusion layer integrates multi-modal representations to generate comprehensive diagnostic insights for accurate cancer classification.

The proposed system further includes preprocessing modules for normalization, noise reduction, missing value handling, and feature alignment across different biomedical modalities. The predictive framework supports multi-stage cancer detection, tumor grading, subtype classification, and progression monitoring. The invention is capable of reducing diagnostic errors, improving early-stage detection accuracy, and assisting clinicians in personalized treatment planning.

The invention also provides scalability and compatibility with cloud-based healthcare infrastructures and intelligent medical devices. The proposed framework may be deployed in hospitals, diagnostic laboratories, telemedicine platforms, and clinical decision support systems. By integrating temporal learning and multi-modal biomedical analysis, the invention significantly enhances automated cancer prediction and healthcare analytics.

Objectives of the Invention

1. To develop a deep learning-based predictive framework for accurate cancer detection and classification using multi-modal biomedical datasets.
2. To design an adaptive temporal feature fusion mechanism capable of integrating spatial and sequential biomedical information for improved diagnostic accuracy.
3. To automate feature extraction and representation learning from heterogeneous medical data including imaging, genomic, and clinical datasets.
4. To reduce diagnostic errors and improve early-stage cancer prediction through intelligent multi-modal data analysis.
5. To provide a scalable and efficient predictive system suitable for deployment in real-time healthcare and clinical decision support environments.

Detailed Description of the Invention

The present invention relates to an intelligent predictive system for cancer detection and classification using deep learning and temporal feature fusion methodologies. The system comprises multiple interconnected modules including a biomedical data acquisition module, preprocessing module, feature extraction module, temporal learning module, adaptive fusion module, classification module, and prediction output module.

In one embodiment, the biomedical data acquisition module collects heterogeneous datasets from multiple medical sources including MRI scans, CT scans, PET images, histopathological images, genomic sequencing data, laboratory reports, and electronic health records. The acquired data is stored in a centralized or distributed healthcare repository for further analysis.

The preprocessing module performs image enhancement, normalization, denoising, segmentation, missing value imputation, and feature standardization operations. Medical images are resized and normalized to ensure uniformity across different imaging modalities. Sequential patient records are temporally aligned and encoded into structured representations suitable for deep learning analysis.

The feature extraction module utilizes convolutional neural networks to automatically extract high-level spatial features from biomedical images. In one embodiment, transfer learning techniques may be employed using pretrained deep neural architectures for improving feature representation efficiency. The extracted imaging features are forwarded to the fusion module for integrated analysis.

The temporal learning module processes sequential patient information using recurrent neural networks, Long Short-Term Memory networks, gated recurrent units, or transformer-based architectures. Temporal dependencies among patient visits, disease progression patterns, biomarker changes, and treatment history are learned dynamically to generate temporal feature embeddings.

The adaptive fusion module integrates spatial imaging features, genomic features, clinical records, and temporal representations using attention-based fusion mechanisms. The fusion layer dynamically assigns importance weights to different biomedical modalities based on their clinical relevance. This enables the predictive system to generate comprehensive disease representations for improved diagnostic performance.

The classification module utilizes fully connected deep neural layers and softmax-based prediction functions to classify cancer types, tumor stages, and disease severity levels. The system may support binary classification, multiclass classification, and risk prediction tasks depending on application requirements. The prediction results are displayed through an intelligent clinical decision support interface.

In another embodiment, the invention may incorporate explainable artificial intelligence techniques for improving interpretability of diagnostic outcomes. Visualization methods such as heatmaps, feature importance analysis, and attention score mapping may be utilized to assist healthcare professionals in understanding prediction results.

The proposed invention provides several advantages including improved cancer detection accuracy, enhanced temporal disease modeling, reduced diagnostic complexity, faster prediction capability, and scalability for real-time healthcare applications. The system can be deployed in hospitals, diagnostic centers, telemedicine environments, and cloud-based healthcare infrastructures.

Design

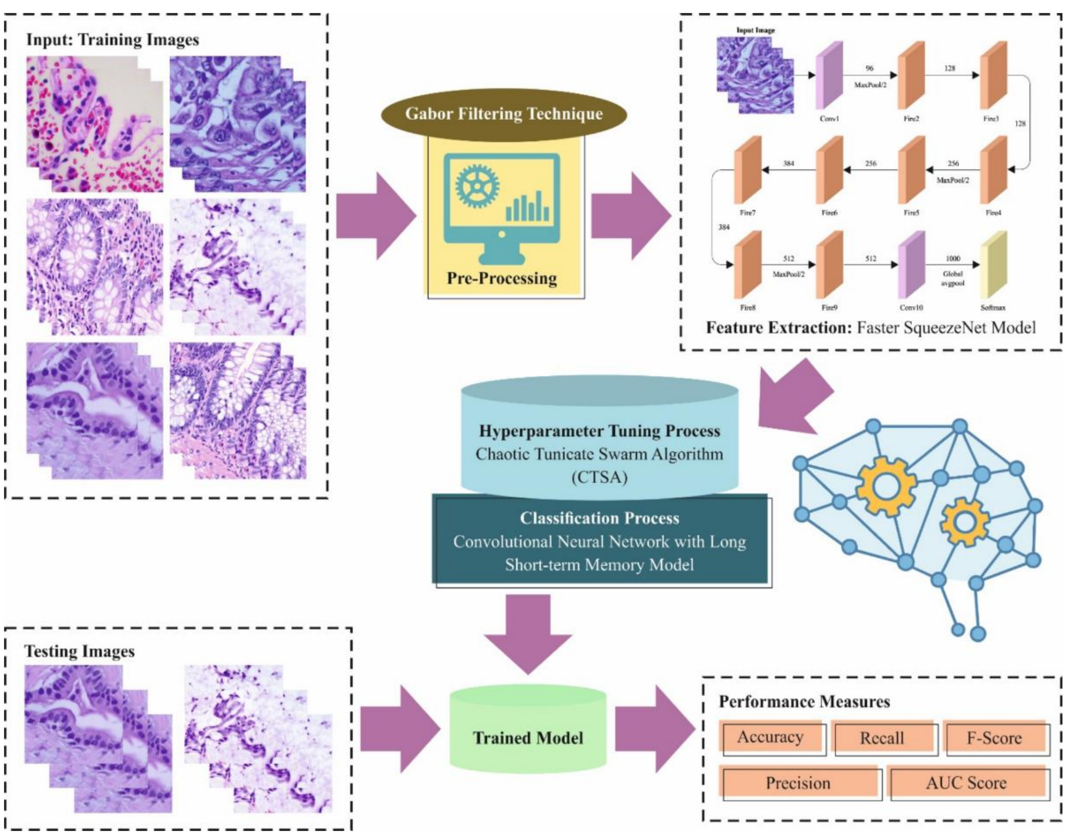

Fig.1. Concept diagram of the proposed invention

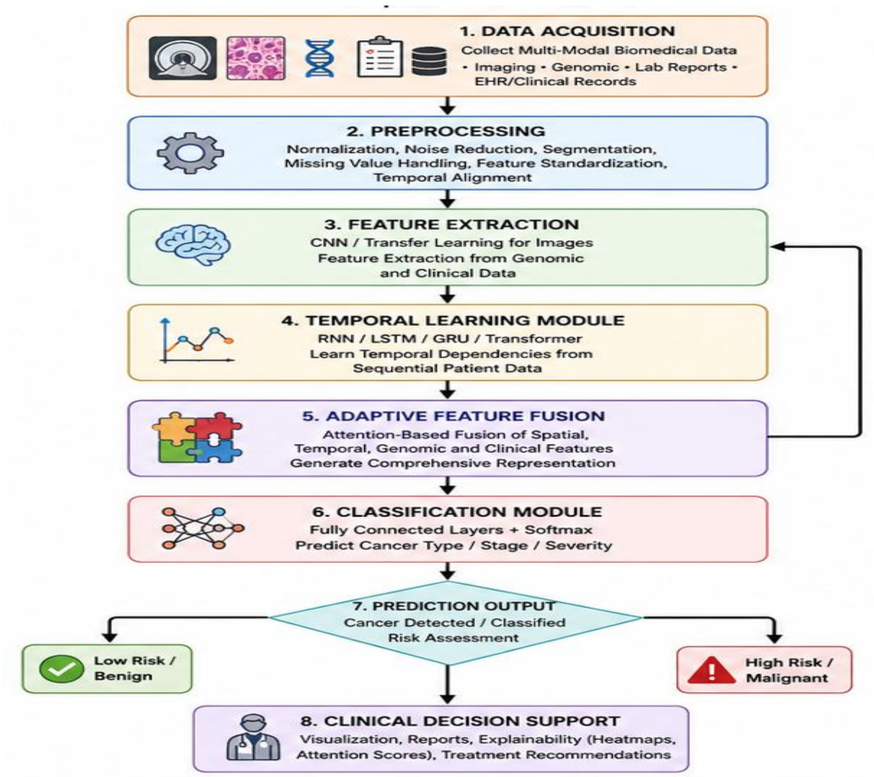

Fig.2. Workflow diagram of the proposed invention

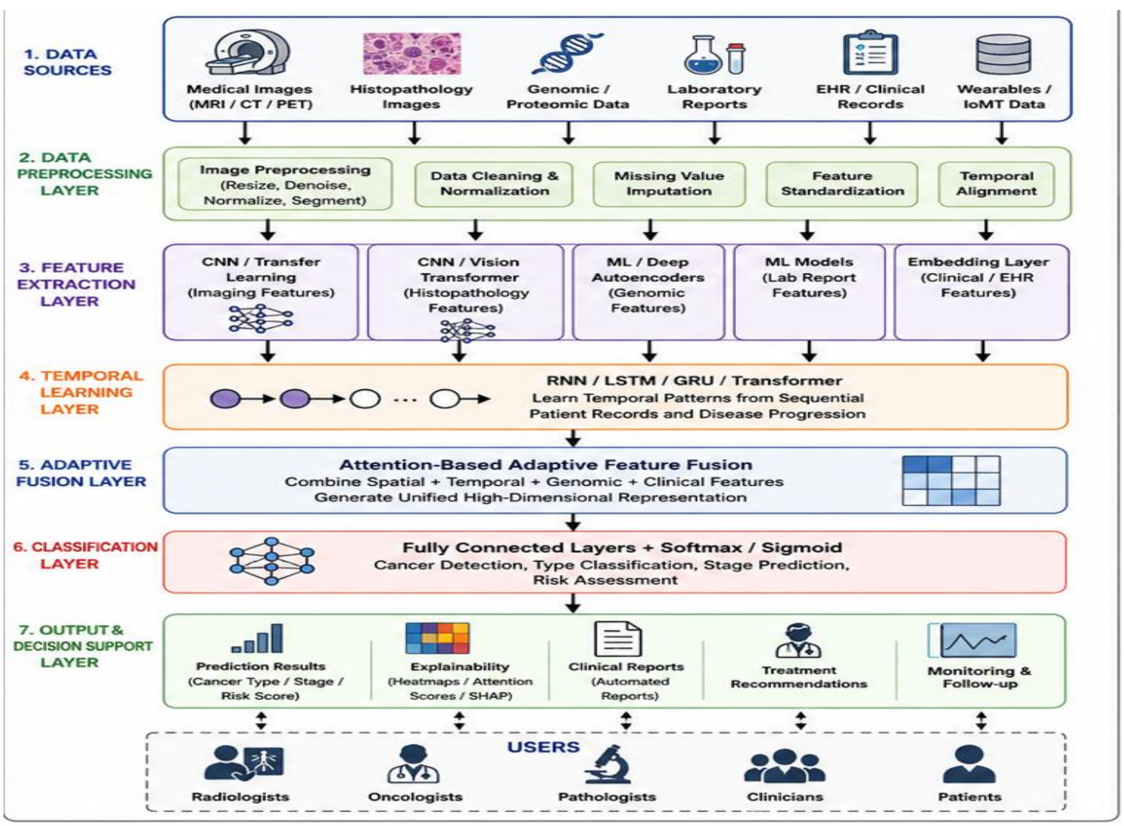

Fig.3. Architecture of the proposed invention

Abstract

The present invention discloses a deep learning-based predictive system for cancer detection and classification using multi-modal biomedical data integrated with temporal feature fusion mechanisms. The system acquires heterogeneous medical datasets including medical images, genomic profiles, laboratory reports, and electronic health records. Advanced deep learning architectures are employed for automatic feature extraction and temporal disease progression analysis. An adaptive feature fusion mechanism integrates spatial and sequential biomedical representations to improve diagnostic accuracy and predictive reliability. The proposed framework supports early-stage cancer detection, tumor classification, progression monitoring, and personalized healthcare decision-making. The invention provides enhanced scalability, reduced diagnostic complexity, and improved performance suitable for real-time healthcare and intelligent clinical environments.

Claims

1. A deep learning-based predictive system for cancer detection and classification using multi-modal biomedical data and temporal feature fusion, comprising:
   a biomedical data acquisition module configured to collect heterogeneous medical datasets including imaging data, genomic data, laboratory reports, and electronic health records;
   a preprocessing module configured to normalize, segment, and standardize the collected biomedical data;
   a feature extraction module configured to extract spatial features using deep neural network architectures;
   a temporal learning module configured to analyze sequential patient information and temporal disease progression patterns;
   an adaptive feature fusion module configured to integrate spatial and temporal biomedical representations; and
   a classification module configured to predict cancer type, stage, or severity based on fused biomedical features.

2. The system as claimed in claim 1, wherein the feature extraction module utilizes convolutional neural networks and transfer learning architectures for automated extraction of imaging features from MRI, CT, PET, or histopathological images.
3. The system as claimed in claim 1, wherein the temporal learning module employs recurrent neural networks, Long Short-Term Memory networks, gated recurrent units, or transformer-based architectures for learning temporal dependencies from sequential biomedical records.
4. The system as claimed in claim 1, wherein the adaptive feature fusion module utilizes attention-based weighting mechanisms to dynamically prioritize clinically relevant biomedical modalities during cancer prediction and classification.
5. The system as claimed in claim 1, wherein the predictive system is integrated with cloud-based healthcare infrastructure and clinical decision support systems for real-time cancer diagnosis, monitoring, and personalized treatment assistance.