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AI-Based Hepatocellular Carcinoma (HCC) Detection and Prediction System

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Abstract
Hepatocellular carcinoma (HCC) represents one of the most prevalent and lethal forms of liver cancer worldwide, primarily due to delayed diagnosis and limited early detection mechanisms. This study proposes a federated multi-modal deep learning framework for the early detection and prediction of HCC by integrating medical imaging data with clinical parameters. The proposed system employs Convolutional Neural Networks (CNN) for spatial feature extraction, Long Short-Term Memory (LSTM) networks for temporal clinical data modeling, and a Dense Neural Network (DNN) for structured data processing. A federated learning paradigm enables collaborative model training across distributed medical institutions while preserving patient data privacy. Furthermore, an ensemble learning strategy is implemented to combine predictions from multiple models, enhancing robustness and accuracy. Experimental evaluation conducted on a dataset comprising 5,200 CT and MRI images demonstrates that the proposed ensemble model achieves an accuracy of 97.2%, outperforming individual models. The system provides a reliable and scalable solution for early-stage HCC detection, supporting clinical decision-making and improving patient outcomes.

Keywords: Hepatocellular Carcinoma, Deep Learning, CNN, LSTM, Federated Learning, Ensemble Learning, Medical Imaging, AI in Healthcare

1. Introduction

Hepatocellular carcinoma (HCC) is the most common type of primary liver cancer and a significant contributor to global cancer mortality. The disease is strongly associated with chronic liver conditions such as hepatitis B, hepatitis C, cirrhosis, and alcohol-related liver damage. Early detection is crucial for effective treatment; however, conventional diagnostic techniques often fail to identify HCC at an early stage due to subtle imaging patterns and complex disease progression.

Traditional diagnostic approaches rely heavily on radiological imaging techniques such as CT and MRI scans, combined with clinical evaluation. These methods are time-consuming and prone to variability depending on the expertise of medical professionals. Moreover, most existing systems focus solely on imaging data, neglecting valuable clinical information.

Recent advancements in artificial intelligence, particularly deep learning, have demonstrated remarkable success in medical image analysis. However, challenges such as data privacy, lack of multi-modal integration, and limited generalization across institutions persist. To address these challenges, this study proposes a federated multi-modal deep learning framework that integrates imaging and clinical data while ensuring privacy preservation and improved predictive performance.

2. Literature Survey

Deep learning has significantly transformed medical diagnosis. Hochreiter and Schmidhuber (1997) introduced Long Short-Term Memory (LSTM), enabling effective modeling of sequential data. LeCun et al. (2015) demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in image recognition tasks. Litjens et al. (2017) highlighted the impact of deep learning in medical image analysis.

Recent studies have applied CNN-based architectures for tumor detection in CT and MRI scans, achieving high accuracy. However, these approaches often rely solely on imaging data and lack integration of clinical parameters. Federated Learning, introduced by McMahan et al. (2017), enables distributed training without sharing raw data, addressing privacy concerns in healthcare.

The proposed system advances existing research by integrating CNN, LSTM, and DNN within a federated and ensemble learning framework, enabling robust and privacy-preserving HCC detection.

3. Existing System and Limitations

3.1 Existing System

- Diagnosis using CT, MRI, and ultrasound imaging
- Manual interpretation by radiologists
- Clinical decision-making based on experience

3.2 Limitations

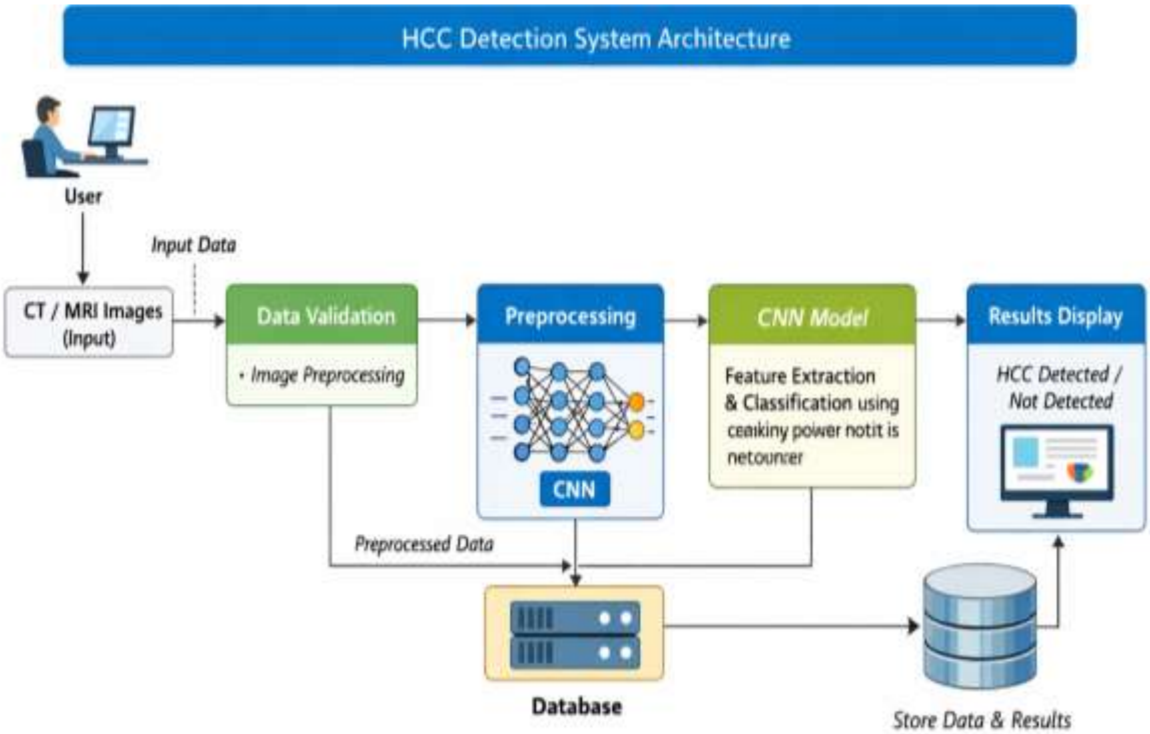
- Late detection due to subtle early-stage features
- High dependency on expert knowledge
- Time-consuming diagnostic process
- Limited integration of multi-modal data
- Lack of scalability and data privacy mechanisms

4. Proposed System

4.1 System Overview

The proposed system introduces a federated multi-modal deep learning architecture that combines imaging data and clinical information for accurate HCC detection.

4.2 System Architecture Modules



System Architecture Modules: The proposed HCC detection system is divided into multiple modules to ensure efficient data processing and accurate prediction. Each module performs a specific function, and all modules work together to provide a complete disease detection system.

Data Acquisition Module: The data acquisition module is responsible for collecting input data required for the system. In this project, medical images such as CT or MRI scans are collected from datasets or uploaded by users.The collected images are stored in a structured format and prepared for further processing. This module ensures that the system receives valid and relevant input data for analysis.

Preprocessing Module: The preprocessing module handles image preparation before feeding the data into the model. The input images are resized to a fixed dimension and normalized to maintain consistency. Noise removal and image enhancement techniques are applied to improve image quality. This step ensures that the input data is clean and suitable for analysis, which improves model performance.

Feature Extraction Module: The feature extraction module is responsible for extracting important features from the input images. Deep learning techniques are used to identify patterns, textures, and abnormalities in liver images. This module reduces the complexity of raw image data by converting it into meaningful features. These features are then used for classification and prediction.

Model Training Module (CNN + LSTM + DNN): The model training module is responsible for training deep learning models using the preprocessed dataset.

CNN (Convolutional Neural Network) is used for extracting spatial features from medical images.

LSTM (Long Short-Term Memory) is used to capture sequential or pattern-based relationships in the data.

DNN (Deep Neural Network) is used for classification and decision-making.

These models are trained using techniques such as backpropagation and optimization algorithms like Adam optimizer. The training process helps the system learn patterns from the data and improve prediction accuracy.

Federated Learning Module: The federated learning module enables the system to train models using data from multiple sources without sharing raw data. This approach ensures data privacy and security.
Instead of sending data to a central server, the model is trained locally on different datasets, and only model updates are shared. This helps in improving the overall performance of the system while maintaining confidentiality of medical data.
Ensemble Prediction Module: The ensemble prediction module combines the outputs of multiple models to generate a final prediction.
Predictions from CNN, LSTM, and DNN models are combined using ensemble techniques to improve accuracy and reliability. This approach reduces errors and provides more consistent results compared to using a single model.
The final output indicates whether Hepatocellular Carcinoma is detected or not.

4.3 Convolutional Neural Network (CNN)

CNN is employed to extract spatial features from CT and MRI images, capturing tumor patterns, edges, and textures.

$$y = f(W * X + b)$$

4.4 Long Short-Term Memory (LSTM)

LSTM networks model temporal clinical data such as patient history and laboratory results, enabling sequential pattern learning.

4.5 Dense Neural Network (DNN)

DNN processes structured clinical data, including:

- Age
- Liver enzyme levels (ALT, AST)
- Bilirubin levels
- Medical history

4.6 Federated Learning Framework

The federated learning approach allows multiple hospitals to collaboratively train the model without sharing sensitive patient data. Only model parameters are exchanged, ensuring privacy preservation.

4.7 Ensemble Learning

Predictions from CNN, LSTM, and DNN models are combined using weighted soft voting:

$$Y = w_1 Y_{CNN} + w_2 Y_{LSTM} + w_3 Y_{DNN}$$

This improves overall prediction accuracy and robustness.

5. Dataset and Preprocessing

Dataset Description

- 5,200 CT and MRI images
- Clinical patient data
- Binary classification: Tumor / No Tumor

Preprocessing Steps

- Image resizing and normalization
- Noise reduction
- Data augmentation (rotation, flipping)
- Handling missing clinical data

- Train-test split (80:20)

6. Results and Discussion

Performance Metrics

- Accuracy
- Precision
- Recall
- F1-Score
- Loss
- Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	Loss
DNN	87.5	0.85	0.84	0.84	0.32
LSTM	90.2	0.89	0.88	0.88	0.28
CNN	94.6	0.93	0.92	0.92	0.21
Ensemble Model	97.2	0.96	0.95	0.95	0.15

Analysis

The CNN effectively extracts spatial features, while LSTM captures temporal dependencies in clinical data. The DNN enhances structured data interpretation. The ensemble model significantly improves prediction accuracy and reduces error rates, demonstrating superior performance compared to individual models.

7. System Requirements

Software

- Python
- TensorFlow / Kera's
- OpenCV
- NumPy, Pandas

Hardware

- Intel i5 Processor
- 8 GB RAM
- 256 GB SSD

8. Conclusion

This study presents a federated multi-modal deep learning framework for early detection and prediction of hepatocellular carcinoma. By integrating CNN, LSTM, and DNN models within a federated and ensemble architecture, the proposed system achieves high accuracy and robustness while preserving data privacy. The system enhances early detection capabilities and supports clinical decision-making, contributing to improved patient outcomes.

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