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A new approach to early Diagnosis of Lung Cancer Employing Neural Networks Utilising Hybrid Deep Learning

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Abstract: Lung cancer is the leading cause of cancer-related deaths worldwide, primarily due to its late-stage diagnosis and aggressive progression. This research presents a new approach to improving the accuracy & timeliness of lung cancer diagnoses: Cancer Cell Detection utilising Hybrid Neural Network (CCDC-HNN). Applying a hybrid deep learning framework, the suggested model processes CT scan data using the LIDC-IDRI, which stands for Lung Image Database Consortium & Image Database Resource Initiative. In order to improve patient survival rates, feature extraction is done utilising deep neural networks with an emphasis on early-stage detection. To increase diagnostic accuracy, the system incorporates a 3D Convolutional Neural Network (3D-CNN). This method successfully distinguishes between benign & malignant tumours, and its efficacy is confirmed by utilising established statistical measures. The suggested hybrid deep learning method for early diagnosis of lung cancer has been shown to be both effective & reliable according to experimental data.

Keywords: Lung Cancer, Neural Network, CT scan images, Hybrid DL Technique, CNN–RNN System

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INTRODUCTION

Lung cancer continues to be one of the most lethal forms of cancer globally, accounting for a significant portion of cancer-related deaths each year. Its high mortality rate is largely attributed to the difficulty of detecting the disease in its early stages, when it is most treatable. Traditional diagnostic methods, including manual examination of CT scans and histopathological analysis, are often time-consuming, prone to human error, and limited in their ability to detect subtle indicators of early-stage malignancy.

Recent advancements in artificial intelligence (AI), particularly deep learning, have shown great promise in automating medical image analysis and improving diagnostic accuracy. Convolutional Neural Networks (CNNs) have become the foundation of many image-based diagnostic systems, excelling at extracting complex features from medical scans such as X-rays and CT images. However, these approaches often rely solely on spatial data and fail to incorporate temporal or contextual patient information, which can be crucial in understanding disease progression.

To address these limitations, this study proposes a novel hybrid deep learning framework—CCDC-HNN—that combines the strengths of CNNs &RNNs, including LSTM units, to enhance the early diagnosis of lung cancer. By leveraging 3D-Convolutional Neural Networks (3D-CNNs) for volumetric feature extraction from CT scans and integrating sequential clinical data through RNNs, the proposed model aims to capture both spatial & temporal patterns associated with cancer development.

The system is trained and evaluated using the publicly available LIDC-IDRI dataset, which provides annotated CT scan images for robust model training and validation. Through extensive experimentation and performance evaluation using standard metrics includes accuracy, sensitivity, specificity, & AUC-ROC, this research demonstrates that the hybrid architecture significantly improves diagnostic outcomes compared to conventional approaches.

LITERATURE REVIEW

Omar Khouadja et al. (2024) A major step forward in healthcare technology is the use of hybrid neural networks for cancer diagnosis. This research provides a thorough analysis of the development, integration, and possibilities of hybrid neural networks with respect to various cancer kinds. By examining their flexibility and effectiveness, apart from imaging modalities, this study aims to give a comprehensive grasp of their role in early detection and tailored cancer management. Insights into future possibilities for improving cancer treatment outcomes through the use of hybrid neural networks are offered in the paper.

Jalu Nusantoro et al. (2024) Among all diseases, lung cancer is extremely common. Preventing lung cancer requires early detection. But this traditional method of diagnosis, carried out by trained medical professionals, can be time-consuming and inaccurate at times. Consequently, to address these issues, a new system utilising CAD (Computer-Aided Detection) is required. CAD's classification strategy is mostly based on deep learning. It takes a lot of expertise and careful observation to choose a classification strategy that works for the research goals. Consequently, new information and ideas for studies are generated by this comprehensive literature analysis. For the purpose of selecting an effective and appropriate method of categorisation and evaluation for the purpose of identifying lung cancer from CT scans. Based on Okoli's methodology, we systematically reviewed the existing literature. The purpose of this study was to compile relevant material on the topic of lung cancer diagnosis using deep learning classification algorithms. This systematic literature review goes on to talk about how to apply the right evaluation methods. This paper's findings include an analysis and set of suggestions for classification methods based on how often each method has been used in prior research. Researchers will also get some further insight into the topic of evaluation methods through an analysis of the categorisation model assessment method.

Ahmed A. Alsheikhy et al. (2023) Cancer of the lung typically begins in the lining of the air sacs and then spreads to other parts of the lung. Globally, this cancer is said to be the deadliest form of the disease. On top of being the deadliest, it also happens to be the most prevalent kind of cancer. Approximately 47,000 people are diagnosed with it every year across the globe. A workable and entirely automated method for detecting & categorising lung cancer is suggested in this article. The goal of this approach is to find cancer earlier so that more people can be saved or fewer people will die from it. It makes use of VGG-19, a deep convolutional neural network (DCNN) method, and LSTMs, another deep learning method. Once modified and combined, the two instruments can identify and categorise lung malignancies. It also makes use of picture segmentation methods. The term CAD describes this system. Employing both tools together, this approach delivers more than 98.8% accuracy, according to multiple studies conducted on MATLAB. A number of methods were devised to assess the disease under consideration. To train, test, and confirm the algorithm's correctness, three lung cancer datasets were utilised. These datasets were obtained from the LUNA16 grad challenge & Kaggle website. Finally, the suggested method is compared to a few existing literature reviews. Accuracy, recall, precision, & F-score are the four performance indicators that are the centre of this examination. By integrating VGG-19 with LSTMs, this system was able to attain an impressive 99.42% accuracy, as well as 99.76% recall, 99.88% precision, and 99.82% F-score. Not only that, but the suggested algorithm beats the competition and yields stunning results, according to the comparison evaluation. The results of this study show that this model can be used to help doctors make more accurate diagnoses of lung cancer. Compared to previous models that have been put into practice, this research shows that the one that was presented has more usefulness, competence, and value.

Imran Shafi et al. (2022) Due to the lack of symptoms, inital-stage lung cancer is difficult to diagnose using computed tomography (CT), which exposes patients to radiation repeatedly and is expensive. Even for experts, reviewing CT scans of the lungs for signs of pulmonary nodules—particularly cell lung cancer lesions—is a time-consuming and error-prone process. In this research, we provide a support vector machine (SVM) model that incorporates deep learning for cancer diagnosis. The suggested CAD model locates the pathological and physiological alterations in the cross-sectional soft tissues of lung cancer lesions. The initial step in training the model to detect lung cancer is to measure and compare the selected profile values in CT images taken at diagnosis from both patients with the disease and healthy controls. The next step is to validate and test the model with CT images of patients and control patients that were not used during training. Using the open-source LIDC/IDRI database, the research looks into 888 annotated CT scans. Pulmonary nodule detection, an indicator of early-stage lung cancer, is 94% accurate using the suggested deep learning-assisted SVM-based model. In terms of identifying nodules in CT scans of the lungs, it performs better than rival systems that utilise hybrid methodologies and more sophisticated DL and ML algorithms. The experimental results show that the suggested method can help radiologists find lung cancer early on, which means patients can be treated more quickly.

According to **Pallavi Tiwari and colleagues (2022)** When it comes to common causes of death in both children and adults, brain tumours rank tenth. Different forms of tumours exist according to texture, area, and shape; however, survival rates are quite low for all of them. The worst-case scenario can result from incorrect categorisation. This is where multiclass categorisation comes in handy; these needed to be appropriately separated into the many classes or grades. The gold standard for depicting the human brain in order to detect different types of tumours is magnetic resonance imaging (MRI) photos. Since convolutional neural networks (CNNs) have recently emerged as the gold standard for picture classification, this research employs them to solve the problem of brain tumour classification. The suggested model accurately classified the brain image into four categories: no tumour (meaning the brain MRI does not contain a tumour), glioma, meningioma, and pituitary tumour. With this model, we get a 99% success rate.

OBJECTIVES

1. To study the hybrid deep learning framework combining CNNs and RNNs, to enable early-stage lung cancer detection from CT scans with high accuracy.

2. To extract image features using deep neural networks—leveraging an advanced 3D-CNN for spatial

analysis—and employ the hybrid architecture to differentiate between benign and malignant nodules.

3. To assess the proposed model's performance using established statistical metrics (e.g., accuracy, sensitivity, specificity) to demonstrate its feasibility for timely lung cancer diagnosis.

METHODOLOGY

In this study, a hybrid deep learning approach combining CNNs and RNNs is proposed to evaluate digital histopathology images, which typically contain dense and complex pixel-level information. The CNN–RNN architecture is designed to influence the strengths of both models: CNNs for spatial feature extraction & RNNs for capturing sequential or structural dependencies within the image data.

Overview of the Proposed Framework

The methodology involves a two-stage process:

Feature Extraction with CNN: The input histopathological images are first processed using a CNN to extract high-dimensional spatial features. These features represent local patterns such as cell shape, texture, and tissue architecture that are relevant for cancer detection.

Temporal Modeling with RNN: An RNN is trained using the retrieved characteristics to represent the interrelationships & contextual connections between various image regions. This step helps in aggregating localized features to generate a global representation, enabling more accurate classification decisions.

Dataset Description

The collected images were derived from paraffin-embedded tissue blocks that had been formalin-fixed and utilised to identify skin cancer. The Genome Sequencing database, which offers annotated high-resolution histology slides for research, is where these images were sourced from.

Application to Melanoma Diagnosis

Although the primary focus is on lung cancer in the broader research, this specific methodology was initially validated on melanoma tumor datasets to ensure its robustness. The hybrid CNN–RNN model was trained to classify histological images into malignant or benign categories based on visual and contextual cues within the tissue structure.

HYBRID CLASSIFIER

The proposed classification model employs a hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to classify medical images into three categories: normal, benign, and malignant. This integrated approach enhances both spatial feature extraction and temporal feature correlation, offering a comprehensive analysis of input images.

CNN-RNN Hybrid Design

The architecture is designed using an optimized hidden layer strategy, where CNNs serve as the primary spatial feature extractor and RNNs (including LSTM and GRU variants) handle sequential dependencies and decision refinement. The final output is derived by logically combining the CNN and RNN classification results.

Convolutional Neural Networks (CNN)

Using a layered structure that includes CNNs, histological or mammographic pictures can have hierarchical characteristics extracted from them:

Convolutional Layers: These layers act as feature extractors, learning pixel-level representations using convolutional filters. A typical 2D convolution is applied to the image X, producing an output feature map Co:

Where:

f is the activation function (e.g., ReLU or Sigmoid), is the feature map filter, and$*$ denotes the convolution operation.

Pooling Layers: Max-pooling operations reduce spatial dimensions while retaining essential features, ensuring spatial invariance to translation and deformation.

Fully Connected Layers: These layers combine and procedure the extracted features to generate high-level abstract representations used for classification.

An advanced representation of the convolutional output at layer CLCLCL is:

$$\mathrm{CoCL} = f(i = 0\prod \mathrm{Ci}^{\mathrm{CL}-1} - 1 * \mathrm{KN}_i^{\mathrm{CL}} + j = 0\prod \mathrm{MAB}_j^{\mathrm{CL}})$$

Where:

- $\mathrm{Ci}^{\mathrm{CL}-1}$: output of the previous convolutional layer,
- $\mathrm{KN}_i^{\mathrm{CL}}$: kernel weight,
- $\mathrm{AB}_j^{\mathrm{CL}}$: additive bias,
- N, M: number of input channels & processing layers, respectively.

Recurrent Neural Networks (RNN)

RNNs, especially LSTM &GRU networks, are used to model dependencies in sequential data and refine classification results based on learned temporal patterns.

LSTM Networks:LSTM contains three gates—input, memory (cell), and output—that allow it to retain critical information while discarding irrelevant data over time. This mechanism helps resolve the vanishing gradient problem and ensures stable learning.

GRU Networks:GRUs are a simplified variant of LSTM that combine the forget and input gates into a single update gate. This improves performance by reducing computational complexity. The update gate and recurrent function are defined as:

$$zk = \sigma(W_g^U H_{k-1} + W_h^U G_k)$$

$$rk = \sigma(W_r^U H_{k-1} + W_s^U G_k)$$

Where:

$W_g^U, W_h^U, W_r^U, W_s^U$: learned weight matrices,

G_k: input at step kkk,

H_{k-1}: previous hidden state.

The final hidden layer output is calculated as:

$$\widehat{H_k} = H_{k-1} + z_k \cdot \widetilde{H_k}$$

Where $\widehat{H_k}$ is the candidate activation computed using the recurrent connections.

Final Classification Strategy

The outputs from the CNN and RNN modules are fused using a logical AND function to ensure that the final prediction incorporates both spatial (image-based) and sequential (temporal/contextual) information. This dual validation mechanism improves classification reliability.

Classes Predicted: The system classifies input images into three categories:

1. Normal – no signs of malignancy or abnormality,
2. Benign – non-cancerous but potentially concerning growths,
3. Malignant – cancerous growths requiring immediate medical attention.

Training Process

The entire hybrid network is trained using supervised learning with backpropagation, optimized via techniques such as Adam optimizer or Stochastic Gradient Descent (SGD). Both CNN and RNN weights are updated during training to minimize classification error.

By combining the localized pattern recognition capabilities of CNNs with the sequence modeling strengths of RNNs, the proposed hybrid classifier significantly enhances diagnostic performance, particularly in distinguishing between early-stage malignancies and benign abnormalities.

DATA PREPARATION

This study utilizes the LUNA16 dataset, a curated subset of the publicly available LIDC-IDRI dataset, which provides high-quality, annotated CT scan data specifically for lung nodule analysis. The LUNA16 dataset is derived from 888 patient scans and includes both CT images and detailed annotations of lung nodules, including their coordinates, diameters, and malignancy ratings.

Dataset Overview

- **Dataset Source:** LIDC-IDRI (via LUNA16 challenge)
- **Subjects**: 888 patients
- **Image Format:** CT scan slices of resolution 512 × 512 pixels
- **Slice Count per Scan:** Ranges between 100 and 400 slices
- Training/Validation Split:
  - Training samples: 710
  - Validation samples: 178

Each CT scan includes labeled information for nodule location (center coordinates) and estimated diameter. These annotations are essential for training a reliable nodule detection model.

Preprocessing Pipeline

A comprehensive preprocessing of three-dimensional CT scan pictures is the first stage in the CAD system that has been proposed:

1. Segmentation – Isolating lung regions from the surrounding tissues.
2. Normalization – Standardizing intensity values across scans.
3. Noise Removal – Reducing artifacts and enhancing signal-to-noise ratio.
4. Grayscale Conversion – Simplifying data while retaining structural information.
5. Image Enhancement – Improving visual clarity and contrast for better feature extraction.

Region of Interest (ROI) Identification

Initial attempts to input entire pre-processed 3D CT images into a 3D Convolutional Neural Network (3D-CNN) produced suboptimal results. To improve performance, a refined strategy was implemented:

- U-Net Architecture was employed to segment and identify Regions of Interest (ROIs), specifically focusing on lung nodules.
- The U-Net was trained using LUNA16 annotations to locate nodule candidates accurately.

Only the ROIs detected by U-Net were used as input to the 3D-CNN, greatly enhancing the model's focus and efficiency.

Nodule Classification and Labeling

The LIDC-IDRI annotation protocol categorizes nodules on a scale from 1 to 5 based on malignancy likelihood:

- Labels 1–2: Likely benign
- Label 3: Uncertain or indeterminate
- Labels 4–5: Likely malignant

To address ambiguity with label 3, two approaches were explored:

1. **Benign Classification:** Assigning label 3 to the benign group (alongside 1 and 2).
2. **Malignant Classification:** Assigning label 3 to the malignant group (alongside 4 and 5).

For consistency, nodules smaller than 3 mm were excluded due to their low clinical significance. The selected nodules ranged in size from 3 mm to 30 mm.

Normalization and Morphological Analysis

To standardize input size for model training:

A 56 × 56 normalization window was applied, ensuring all nodules fit within a fixed input size. This decision was based on the observation that no nodule exceeded 55 pixels in diameter.

Additionally, lung nodules were categorized based on morphology into five distinct types, aiding the model in learning diverse patterns associated with nodule shapes and growth behaviors. Representative samples of each nodule type are illustrated in Fig. 3, supporting the visual differentiation required for accurate classification.

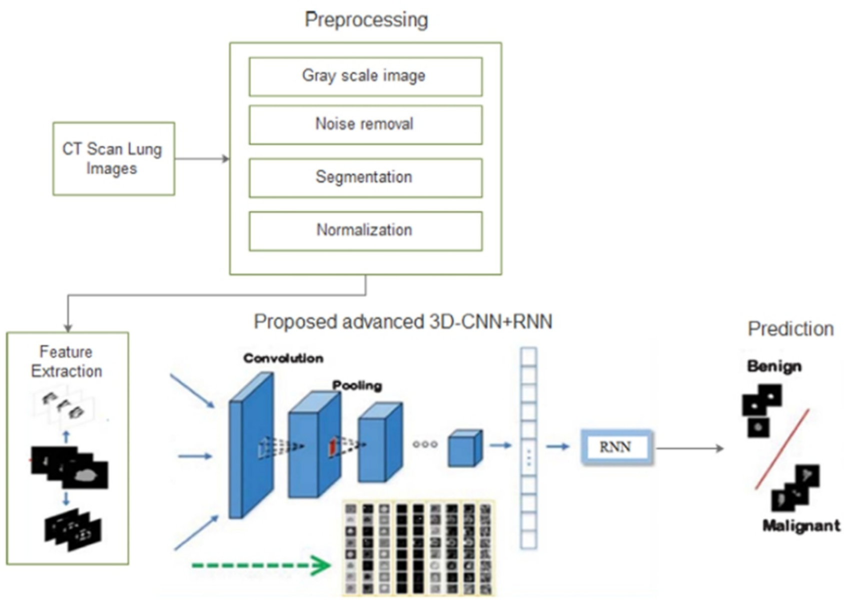

Figure 1:Proposed model of 3D-CNN+RNN

Feature extraction

An essential part of the diagnostic process, feature extraction enables the system to extract the most useful information from CT scans of the lungs.These features, derived from both the geometric and intensity aspects of lung nodules, offer a comprehensive representation of the data. Geometric features such as shape, size, roundness, and surface irregularities help describe the physical structure of nodules, while intensity-based features, including mean intensity, contrast, and texture, provide valuable insight into tissue density and internal composition. Together, these attributes serve as the foundation for differentiating between benign and malignant nodules. Once these features are extracted, they are fed into a classification model during the training phase, enabling the system to learn and recognize patterns associated with cancerous and non-cancerous nodules. In the testing phase, the model applies this learned knowledge to predict the malignancy status of new, unseen nodules. This process ensures that the model can generalize well to real-world clinical data. Overall, the feature extraction stage transforms raw medical images into structured, meaningful data that significantly improves the performance of deep learning models in early lung cancer detection.

ADVANCED 3D CONVOLUTIONAL–RNN FOR LUNG CT CANCER DETECTION

The proposed approach integrates an advanced 3D-CNN with a RNN to accurately classify lung nodules detected in CT scan images. Once potential nodules have been segmented and identified as regions of interest (ROIs), the system proceeds with classification to determine whether the nodules are benign or malignant. The system's capacity to grasp spatial & sequential correlations in visual data is improved by the hybrid 3D-CNN+RNN model.

In the 3D-CNN architecture, various convolutional layers with kernel sizes of 3×3×3 are employed to extract rich spatial features, while 2×2×2 kernels are used in pooling layers to reduce the dimensionality and preserve significant features. The number of feature maps (filters) used in successive convolutional layers is set to 96, 128, 256, 324, and 512, respectively. The input to the network consists of volumetric CT scan images with dimensions 227×227×227, which are processed by the first convolutional layer with 96 filters. As the data passes through deeper layers, max-pooling operations progressively reduce the spatial dimensions, enhancing computational efficiency and minimizing overfitting.

After the convolutional stages, fully connected layers are used to integrate high-level abstract features, which are then passed to the RNN component of the model. The RNN, which excels in handling temporal and sequential information, uses the outputs of the CNN layers as input and applies the same parameters across all time steps or hidden layers. This recurrent processing allows the model to capture contextual relationships and dependencies between features extracted from different slices or regions of the CT scans.

By combining the spatial learning power of 3D-CNNs with the sequence modeling capabilities of RNNs, the system significantly improves the classification accuracy of lung nodules. The model effectively distinguishes between normal and malignant tissue, contributing to improved early detection, diagnosis, and clinical decision-making in lung cancer care.

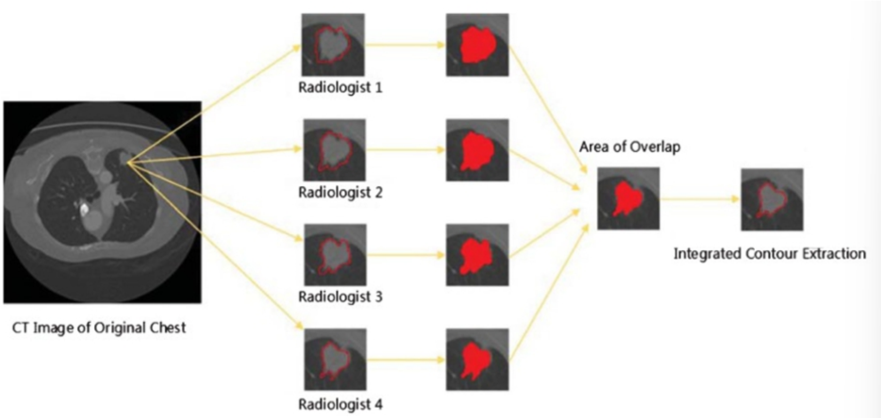

Figure 2:Process of ROI extraction

Training model

The proposed architecture consists of several key components: a pre-trained convolutional neural network (CNN) layer, a recurrent neural network (RNN) layer, a fusion (merging) layer, and a fully connected layer that culminates in a Softmax activation for final classification. When training a model, backpropagation is typically the technique of choice for maximising its performance. In order to make sure the model learns more and better over time, the weights in each layer are adjusted depending on the difference between the expected and actual results.

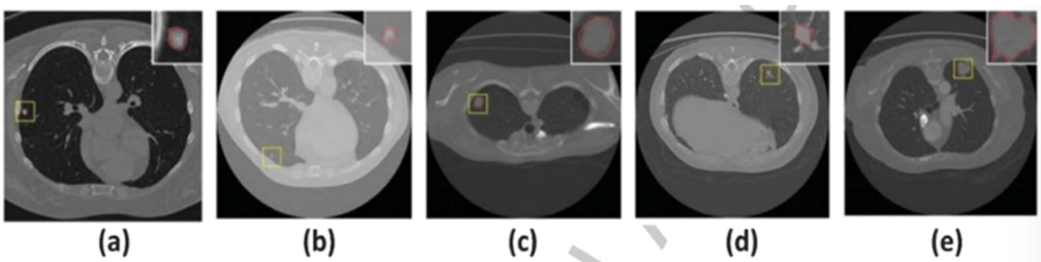

Figure 3:Nodule morphology in the lungs

The proposed system incorporates a pre-trained CNN layer that leverages feature weights obtained from prior training on the ImageNet dataset. This initialization enhances the model's efficiency by utilizing learned patterns from a vast database. The CNN structure includes key components such as convolutional layers and pooling layers. The convolutional layer performs feature extraction by applying convolution windows—typically of size 3×3 or 5×5—across the input features using filters to capture spatial hierarchies. Activation functions are applied to these outputs to introduce non-linearity. Pooling layers, on the other hand, reduce the spatial size of the feature maps using sliding windows (commonly 2×2 with a stride of 2), which decreases the number of parameters and accelerates training. The system uses ReLU as its activation function and employs the Xception model, an enhanced version of Inception v3, which replaces standard convolutions with depth-wise separable convolutions for improved performance. The architecture also includes a recurrent neural network (RNN) layer, which models sequential dependencies by feeding hidden state outputs back into the network. Unlike standard RNNs, this model utilizes LSTM units, which manage information flow through input, forget, and output gates. These units retain important temporal information and discard irrelevant data, allowing the system to capture long-term dependencies effectively. Next, a merge layer is used to enable the model to learn sequential & spatial patterns simultaneously. It does this by combining the features generated by the CNN & RNN branches utilising element-wise multiplication. A fully connected layer with a Softmax function is used to generate a probability distribution across output classes from the combined features. To measure how well the model trained, cross-entropy is employed as the loss function. For training, the CNN component begins with pre-trained weights while the RNN initializes parameters randomly. Initially, the CNN layer is frozen to allow the RNN to stabilize; then, the entire network is trained using the Adam optimizer with a learning rate of 0.001 over 10 epochs. The training concludes once the model achieves its minimum validation loss. For better identification and classification of malignant lung nodules, this state-of-the-art framework called the CCDC-HNN combines a 3D CNN with a RNN. The model's effectiveness is later validated through simulations and comparison with a mathematical baseline.

ALGORITHM FLOW

Figure 6 shows the algorithmic approach for the cancer detection system that uses a hybrid neural network.The process begins with acquiring essential input data from the dataset, followed by a preprocessing stage to prepare the data for further analysis. The prepared data is then divided into training and testing sets. The training samples are processed using both Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), enabling the models to learn relevant features and patterns.

During testing, the system evaluates the performance of both models. The predictions from CNN and RNN are merged to generate a comprehensive output, offering a more reliable result. This cycle of prediction and optimization continues iteratively until a predefined performance threshold is reached. Additionally, feedback from the output is used to fine-tune the weights within the hidden layers, thereby enhancing the model's overall accuracy and robustness.

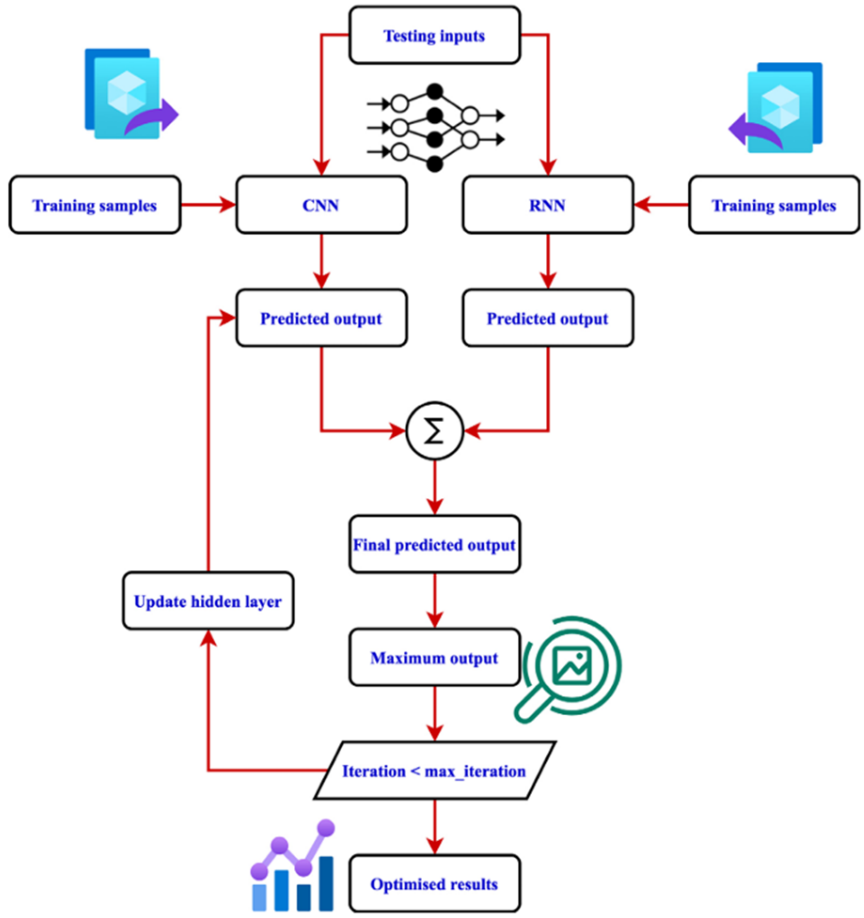

Figure 5:A cancer diagnosis approach based on hybrid neural networks

Time complexity

Layer count, neurone density per layer, input data dimensionality, & activation function specificity are a few factors that impact the computational complexity of DNNs & 3D-CNNs. An operation's time complexity can be determined by dividing the number of forward passes performed during training by the number of operations required for one pass. One of the prevailing challenges in CNN-based systems today is managing this time complexity effectively.

To understand how each hyperparameter impacts the model's efficiency, experts often analyze the time complexity. In this study, minimizing dataset complexity is a key priority to enhance the precision of lung cancer diagnosis. As a solution, a feature selection technique is employed to isolate the most relevant lung-related features from a broader feature set. The time complexity of a fully related layer can be estimated using the formula:

$$TC = \left(\sum \sum ll = 1\, f\, f\, D\, D.W\, W.H\, H.N\, N\right)$$

Here, D signifies the input/output channels, W the input width, H the input height, and **N** the number of output units. Importantly, having more layers does not always equate to higher computational complexity—what matters more is the structure and organization of these layers.

In the proposed framework, both DNN &3D-CNN are leveraged to extract features from CT images and enhance diagnostic accuracy. While the exact architectural details (like the number of layers or neurons) are not specified, it is evident that these models require considerable computational power due to the high dimensionality of medical imagery.

Nevertheless, there are established strategies for reducing the time complexity of deep networks, such as model pruning, parallel computing, and transfer learning. These approaches are part of our planned future work. The current research introduces an innovative hybrid deep learning approach—CCDC-HNN—for the early and accurate detection of lung cancer. The results and performance evaluation of this framework are discussed in the following section.

EXPERIMENTS AND RESULTS

The results of the suggested method are detailed in this section. There are two primary parts to the model:

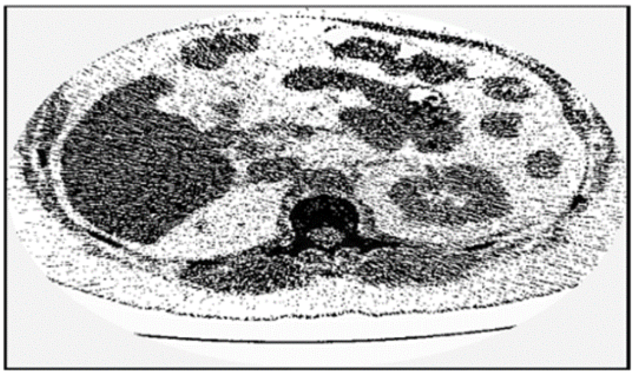

Figure 6(a):Model input.

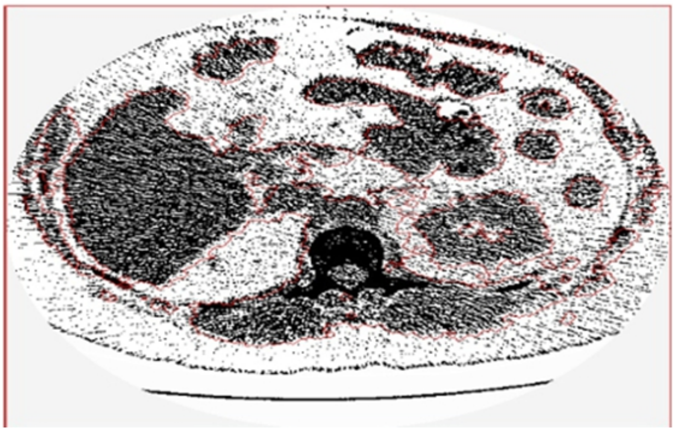

Figure 6(b):Results obtained from running the system model:

PERFORMANCE EVALUATION OF THE PROPOSED CCDC-HNN FRAMEWORK

The proposed HNN model, CCDC-HNN, comprises two primary components:

- **CNN Component:** This segment incorporates the Xception architecture along with domain adaptation techniques. Initially, the classification layer and RNN components are trained while the remaining CNN layers are frozen to stabilize early learning. The optimizer employed for this phase is derived from the dataset referenced in [A. Asuntha 2020].

· **RNN Component:** A Bi-directional LSTM (BiLSTM) network is used to handle the temporal dependencies within the CT image sequences. In the second phase of training, the CNN layers are unfrozen and fine-tuned using the Adam optimizer. This stage also integrates cross-entropy with gradient descent to align the predicted outputs with one-hot encoded probability distributions, enhancing classification performance.

The implementation of the system utilizes Python 3.8.2 on a Windows platform, making it accessible and executable across a range of hardware configurations. The model uses the publicly available LUNA 16 subset of the LIDC/IDRI dataset for CT scan data.

Input/Output and Simulation Details: Figures 8(a) and 8(b) illustrate the CT image input and corresponding output, respectively. The input image, representing a lung with a potential cancerous region, is analyzed through the hybrid 3D CNN-RNN structure to detect malignancies. The model was trained and validated using distinct segments of the LUNA 16 dataset.

RESULTS AND EXPERIMENTS

Simulation results are detailed in Figure 8, showcasing performance metrics including accuracy, precision, specificity, sensitivity, F1-score, & recall. Both training & testing samples were evaluated independently using the hybrid model. Final predictions were made by combining the results from the CNN and RNN branches.

As illustrated in Figure 9, the CCDC-HNN framework consistently demonstrates superior performance across all key evaluation metrics for both training and testing datasets. This proves the effectiveness of the proposed hybrid model in accurate and early lung cancer detection.

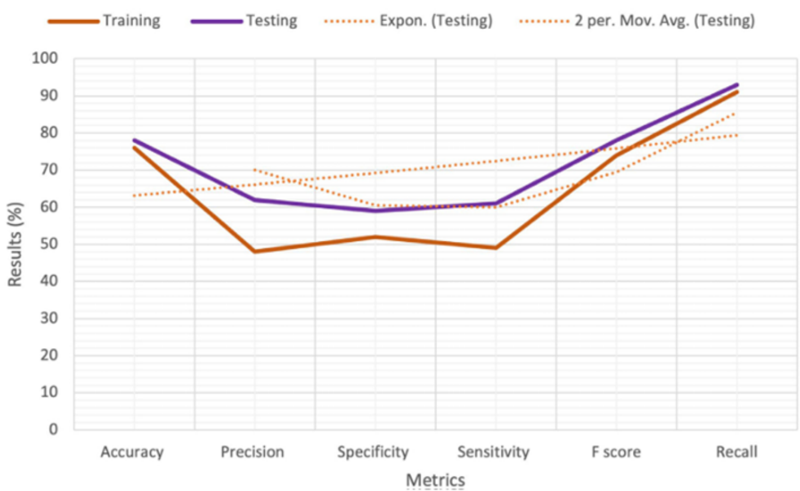

Figure 7:Results from the planned project based on software simulations.

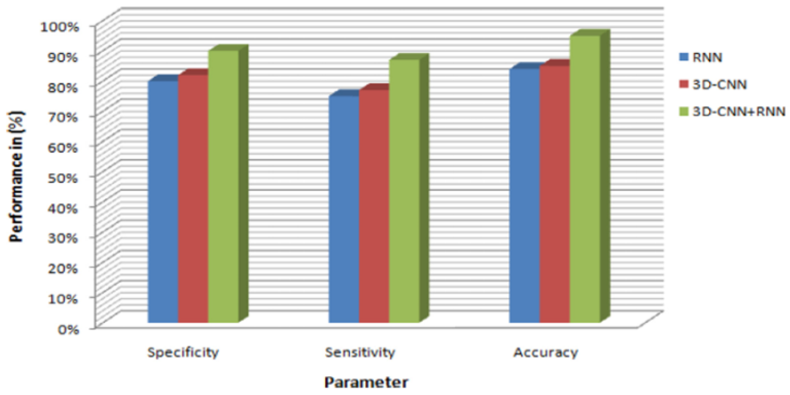

Figure 8:Criteria for evaluating performance

The performance of the proposed CCDC-HNN model has been systematically evaluated and benchmarked against several conventional ML & DL models. These include basic 3D CNN, RNN, and other popular classifiers such as DNN, SVM, Random Forest, & Naïve Bayes.

Hybrid Model Evaluation: The hybrid approach of combining a 3D CNN for spatial feature extraction & RNN for sequence-based classification has demonstrated superior results. The system's software implementation produced output that was quantitatively assessed in terms of specificity, sensitivity, and accuracy—key indicators in medical diagnostics.

Comparative Analysis: Figures 10(a) and 10(b) illustrate the comparative performance across various models. The CCDC-HNN framework significantly outperforms traditional CNN, DNN, SVM, RF, NB, and standalone RNN in terms of:

- Accuracy
- Precision
- Specificity
- Sensitivity

This performance gain is attributed to the synergistic fusion of temporal and spatial feature learning, which enhances both detection and classification phases.

Error and Accuracy Metrics: Further validation is provided in Figures 11(a) and 11(b), which show the trend of accuracy and Mean Squared Error (MSE) over different iterations (ranging from 1 to 10). The results indicate a consistent improvement in prediction accuracy and a corresponding decrease in MSE as the number of iterations increases, highlighting the stability and learning capability of the model.

Through detailed simulation, it is evident that the CCDC-HNN framework delivers improved diagnostic performance. The hybrid combination of CNN and RNN not only refines feature extraction & classification processes but also results in more accurate and reliable predictions for lung cancer detection. This evaluation reaffirms the robustness of the proposed model, especially when compared with existing standalone classifiers and conventional neural networks.

This study underscores the limitations of conventional lung cancer detection techniques, which often fall short in accurately identifying tumor presence and staging. In contrast, the proposed approach introduces an advanced hybrid deep learning framework—the CCDC-HNN model, which integrates a complex 3D-CNN with a RNN—to improve diagnostic accuracy. The method leverages CT scan images from the LUNA 16 dataset to extract meaningful features through a 3D-CNN architecture. These features are subsequently analyzed by an RNN for precise classification of cancerous lung nodules. This dual-network design enables the system not only to detect the tumor effectively but also to assess its stage and count.

Empirical evaluations demonstrate the robustness of the model, yielding are 95% Accuracy (ACC), 90% Specificity (SP) & 87% Sensitivity (SE). These metrics highlight the efficiency of the hybrid model in medical image classification, outperforming traditional techniques significantly. These metrics highlight the efficiency of the hybrid model in medical image classification, outperforming traditional techniques significantly. The CCDC-HNN model delivers a sophisticated yet effective solution for lung cancer detection using CT scans. Its success opens new pathways for clinical implementation, while also laying the foundation for future enhancements through deeper research and development in AI-driven medical diagnostics.

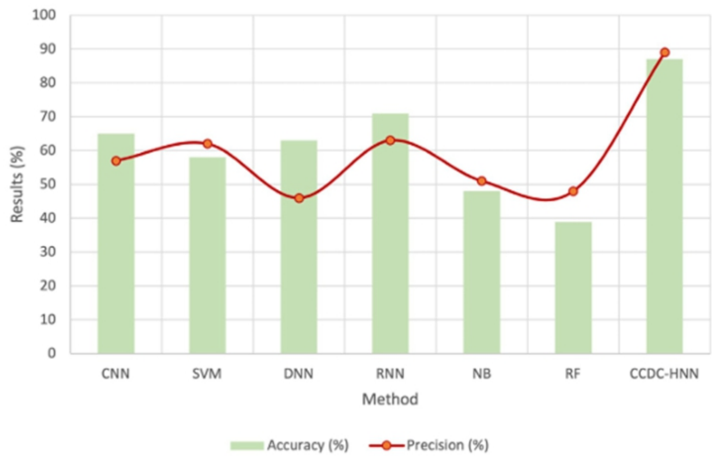

Figure 9(a):Analysing precision and accuracy

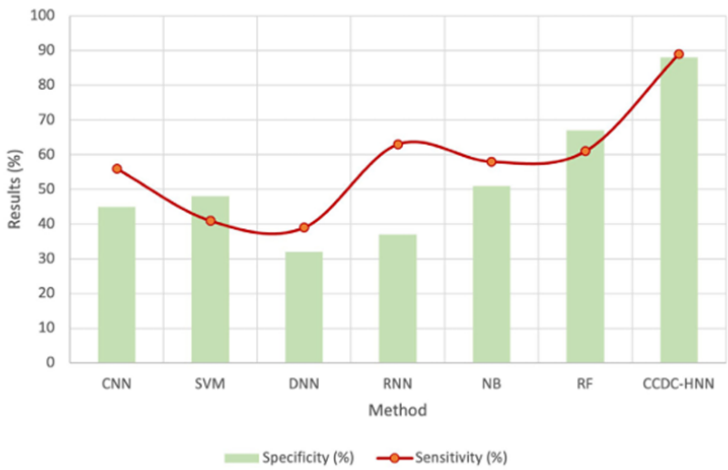

Figure 9(b):Analysing specificity and sensitivity

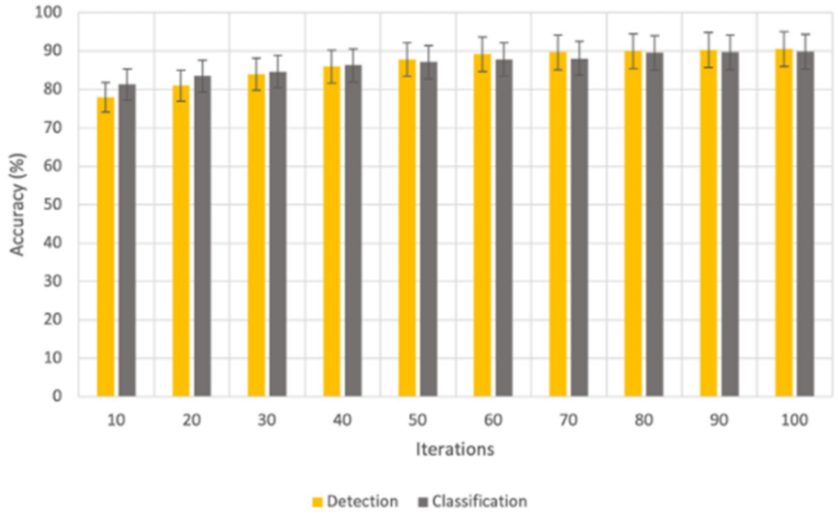

Figure 10(a):Evaluation of the CCDC-HNN architecture for accuracy.

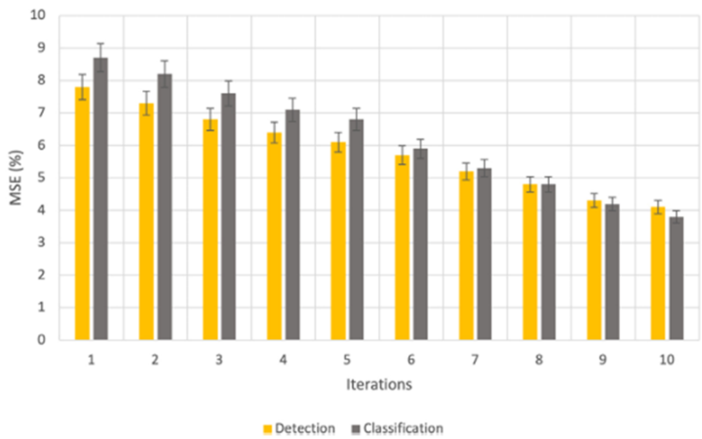

Figure 10(b):Mean squared error evaluation of the CCDC-HNN architecture

CONCLUSION

Lung cancer remains one of the deadliest diseases, underscoring the urgent need for innovative solutions aimed at early detection to improve patient survival rates. This research proposes a cutting-edge approach combining a 3D CNN with a RNN to classify cancerous lung nodules. Leveraging the LUNA 16 dataset, this novel method employs an innovative feature extraction technique to process CT scan images with remarkable accuracy. By integrating a hybrid deep learning framework, the system classifies lung nodules with impressive results: achieving 90% specificity, 87% sensitivity, and 95% accuracy. Looking ahead, there is significant potential to further improve the system's performance. Future advancements could involve the integration of big data analytics and cascaded classifiers, both of which would serve to improve the efficiency and sturdiness of the model for even more reliable lung cancer detection.

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