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"Lung Cancer Detection by integrating U-Net and CNN"

Mirza Yasser Ali Baig [1], Syed Affan Ahmed [2], Mohammed Shahnawaz[3], Dr. S. Madhu[4]

[1,2,3]*UG Scholars,* [4]*Professor*
[1,2,3,4]*Department of CSE(Artificial Intelligence & Machine Learning),*
[1,2,3,4]*Guru Nanak Institutions Technical Campus, Hyderabad, Telangana, India*

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Abstract - *Lung cancer remains a major global health concern due to late-stage diagnosis and limited access to fast, reliable screening tools. This research presents an integrated deep learning framework for automated lung cancer detection using CT scan images. The proposed system combines U-Net for precise segmentation of lung regions with a CNN-SVM hybrid model for accurate binary classification. Preprocessing steps such as resizing, normalization, and augmentation enhance model generalization, while the Adam optimizer and EarlyStopping techniques improve training efficiency. Evaluation results demonstrate high accuracy and stable training behavior. To support practical deployment, a Streamlit-based web application was developed, enabling real-time prediction from uploaded CT images. The framework offers a scalable and accessible solution for improving early lung cancer detection and aiding clinical decision-making.*

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Key Words**:** *U-Net, CNN-SVM, Lung Cancer Detection, CT-Scan, Segmentation, Deep Learning*

1 INTRODUCTION

Lung cancer is among the deadliest cancers worldwide, responsible for approximately 2.2 million new cases and 1.8 million deaths in 2020 alone [1]. In India, the incidence continues to rise, particularly among men and increasingly among women, with nearly half of the cases diagnosed only after reaching advanced stages [2]. Early and accurate detection is critical, as the five-year survival rate can exceed 90% when diagnosed early, compared to just 10–15% in later stages [16].

While low-dose computed tomography (CT) scans are widely used for lung cancer screening, manually interpreting these images is time-consuming, error-prone, and heavily reliant on radiological expertise. The anatomical similarity of malignant nodules to surrounding structures like bronchi and blood vessels further complicates diagnosis, often leading to false positives or delayed detection [11]. These limitations have accelerated the adoption of deep learning techniques in medical imaging, particularly for tasks like tumor localization and classification [7][15].

This research proposes a hybrid deep learning-based framework for automated lung cancer detection using CT images. The system integrates U-Net, a convolutional neural network (CNN) architecture known for precise biomedical image segmentation [10][13][14], with a CNN-SVM pipeline for classification. U-Net first isolates the lung region by segmenting CT images at the pixel level, and the CNN extracts deep spatial features from the segmented output. These features are then fed into a Support Vector Machine (SVM) classifier for binary categorization into cancerous and non-cancerous classes, leveraging SVM's strength in handling high-dimensional data [6][8][17].

To ensure robustness and generalizability, the input images undergo preprocessing steps including resizing, normalization, and augmentation. The model is optimized using the Adam optimizer, with early stopping to prevent overfitting and enhance training efficiency. Evaluation metrics such as Dice coefficient, AUC-ROC, and accuracy are used to assess the model's performance [5][12].

By combining U-Net's segmentation capabilities with CNN-SVM classification, this system aims to offer a reliable and efficient diagnostic tool. Trained on publicly available datasets like LIDC-IDRI [4], the proposed model not only enhances detection accuracy but also reduces diagnostic delays and variability, ultimately contributing to faster clinical decisions and improved patient outcomes [9].

2 LITERATURE REVIEW

Lung cancer remains one of the most fatal malignancies globally, largely due to delayed detection and the difficulty of distinguishing malignant from benign nodules in CT scans. With advancements in artificial intelligence, deep learning has emerged as a transformative approach for medical image analysis, offering increased speed, accuracy, and reproducibility over conventional diagnostic methods [1][3].

A wide range of deep learning models have been applied to lung CT images. Ivusic et al. developed a modified U-Net architecture that achieved improved segmentation of lung nodules, showing the effectiveness of encoder-decoder designs in isolating regions of interest [10]. Similarly, Naseer et al. integrated lobe segmentation with U-Net to enhance both lung localization and nodule classification [11]. Fernandes et al. proposed a two-stage U-Net framework for interactive segmentation, which demonstrated high precision in isolating complex lung structures [12].

Hybrid models combining segmentation and classification have also shown promise. Golkarieh et al. proposed a U-Net architecture coupled with pretrained backbones and a BIR model for robust detection and classification [7]. Sultana et al. compared multiple CNN and hybrid transfer learning models to evaluate classification performance across different lung cancer types [8], while D. S et al. incorporated CNN classifiers on top of U-Net segmented outputs for stage-wise classification [17].

CNNs remain a strong backbone for classification. Abraham et al. demonstrated the potential of CNNs in classifying lung nodules from CT images [4], and Vij and Kaswan validated the use of CNNs for early-stage cancer prediction [6]. Akintola et al. developed an integrated deep learning model using Mask R-CNN for segmentation and CNN for classification, achieving state-of-the-art performance [2]. Jain et al. introduced an attention-enhanced CNN (RCBAM-CNN), showing improved focus on tumor regions through attention mechanisms [1].

In terms of training optimization, Hui et al. presented a multiscale U-Net model incorporating 3D attention and edge perception to better detect nodule boundaries [13]. Alafer et al. explored the L-UNet architecture, which enhanced segmentation reliability for complex medical imaging tasks [14]. Yuan et al. introduced a 3D residual U-Net with multi-branch attention, further refining pulmonary nodule detection [5].

Evaluation metrics such as Dice coefficient, AUC-ROC, and accuracy are widely used to benchmark segmentation and classification models [9][15]. Additionally, training strategies like image normalization, augmentation, early stopping, and the Adam optimizer have been shown to boost generalization and prevent overfitting [16].

Finally, transformer-based and context-aware approaches are gaining traction. Shimazaki et al. applied segmentation-based deep learning on chest radiographs for cancer detection [15], while Durgam et al. proposed a hybrid transformer-deep learning framework that demonstrated improved interpretability and performance [16].

Collectively, these studies highlight the need for an integrated diagnostic pipeline. The current research builds on this by proposing a hybrid deep learning system combining U-Net for segmentation and a CNN-SVM model for classification, using the LIDC-IDRI dataset [4] and standard evaluation protocols to develop a clinically relevant lung cancer detection tool.

3 PROBLEM STATEMENT

Early detection of lung cancer plays a crucial role in improving survival rates, yet current diagnostic approaches remain inadequate for accurate and timely identification. Manual interpretation of CT scans is labor-intensive, susceptible to inter-observer variability, and often fails to detect small or ambiguous nodules in early stages. Traditional machine learning models typically require handcrafted features and lack the precision needed for complex segmentation and classification tasks. This creates a pressing need for an automated, reliable, and scalable solution that integrates advanced deep learning models to segment lung regions and classify nodules accurately. Addressing this gap, the proposed framework combines U-Net for precise segmentation with a CNN-SVM model for effective classification, aiming to support clinicians in making faster and more accurate lung cancer diagnoses.

4 PROPOSED METHODOLOGY

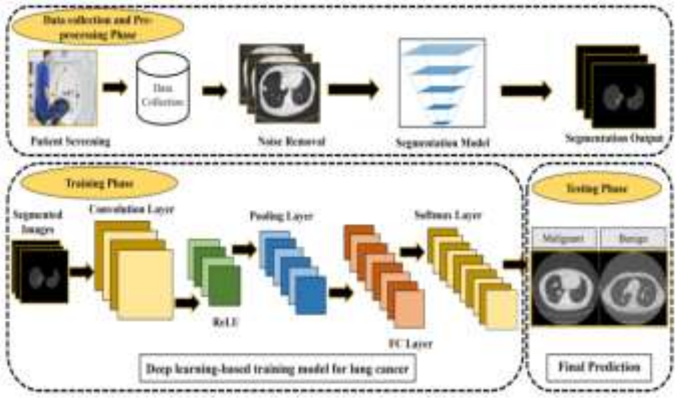

Figure 1: End-to-End Methodology for Lung Cancer Detection [3]

The proposed system is a deep learning-based framework developed to detect lung cancer from CT scan images with high accuracy, automation, and efficiency. It follows a modular pipeline that begins with image preprocessing, where input CT scans are resized, normalized, and optionally augmented to enhance the model's robustness. A U-Net architecture is then employed to perform semantic segmentation, isolating the lung region from the background with pixel-level precision. This step ensures that only the region of interest is passed forward for further analysis, reducing noise and improving feature learning.Following segmentation, the extracted lung region is processed by a Convolutional Neural Network (CNN) that learns deep spatial features indicative of cancerous patterns. These features, instead of being classified by a traditional fully connected Softmax layer (as shown in the reference architecture), are input into a Support Vector Machine (SVM), which performs binary classification to predict the presence or absence of cancer. This hybrid combination leverages the CNN's ability to extract meaningful features and the SVM's effectiveness in handling high-dimensional data with limited samples. Finally, the complete system is deployed through a Streamlit web application, enabling users to upload CT scan images and receive instant diagnostic predictions. This architecture facilitates precise, real-time, and user-friendly diagnostic assistance, offering a strong foundation for clinical decision support in lung cancer screening.

4.1 System Architecture

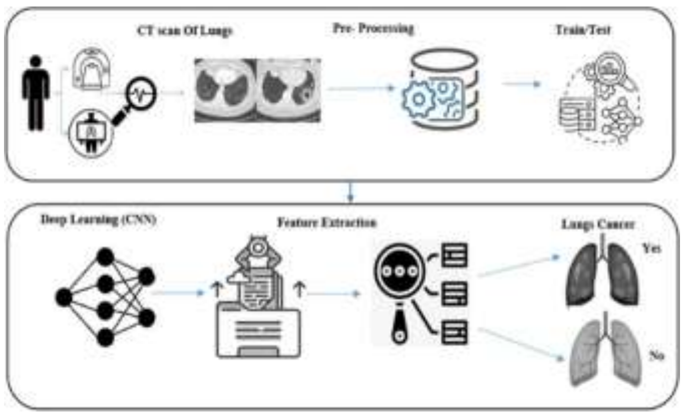

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Figure 2: System Architecture of the Proposed Lung Cancer Detection Model [9]

The system follows a modular, end-to-end pipeline. Initially, raw CT scan images undergo preprocessing to ensure uniformity. These images are then segmented using U-Net to isolate lung regions. The segmented outputs are passed through a CNN for deep feature extraction, and the resulting features are classified using an SVM model. Each component in the architecture is optimized individually and seamlessly integrated to support efficient lung cancer detection.

4.2 Data Description & Preprocessing

This project uses a dataset of lung CT scan images paired with binary masks that delineate lung regions, serving as ground truth for training a U-Net segmentation model. The primary dataset is sourced from a publicly available Google Drive repository referenced in the base GitHub project. Alternatively, the LIDC-IDRI dataset from The Cancer Imaging Archive (TCIA: https://www.cancerimagingarchive.net/collection/lidc-idri/) can be used for research and benchmarking purposes.

All CT images are resized to a uniform 256×256 pixel resolution to ensure consistency across the dataset. Pixel intensities are normalized to a range, and images can be converted to grayscale to reduce computational demands without sacrificing essential spatial information. To enhance model generalization and minimize overfitting, data augmentation techniques such as rotation, flipping, and zooming are applied to the training set. The processed dataset is then split into training and validation sets in an 80:20 ratio, ensuring balanced representation of both cancerous and non-cancerous samples. This standardized preprocessing and augmentation pipeline supports robust and reproducible lung segmentation model development.

4.3 Lung Region Segmentation Using U-Net

The U-Net model is employed to segment and extract lung regions from the CT scans. Its encoder-decoder structure with skip connections allows it to capture both global context and fine-grained anatomical details. The output is a binary mask that highlights the lung fields, filtering out irrelevant structures and improving downstream feature extraction.

4.4 Feature Extraction Using CNN

Once segmentation is complete, the binary-masked lung images are processed by a CNN. The CNN autonomously learns critical spatial features such as texture, shape, and edge patterns that are often indicative of malignancy. This eliminates the need for manual feature engineering and provides a rich feature set for classification.

4.5 Binary Classification Using SVM

The extracted CNN features are fed into a Support Vector Machine (SVM) for binary classification. The SVM determines whether the input corresponds to a cancerous or non-cancerous region. It is chosen for its high accuracy on small, high-dimensional datasets and its ability to construct optimal decision boundaries in feature space.

4.6 Training and Optimization Strategy

The Adam optimizer is utilized during training to achieve faster and more stable convergence through adaptive learning rates. Additionally, an EarlyStopping mechanism is implemented to monitor validation loss and halt training when improvements stagnate, thereby preventing overfitting and reducing computational costs.

4.7 Workflow

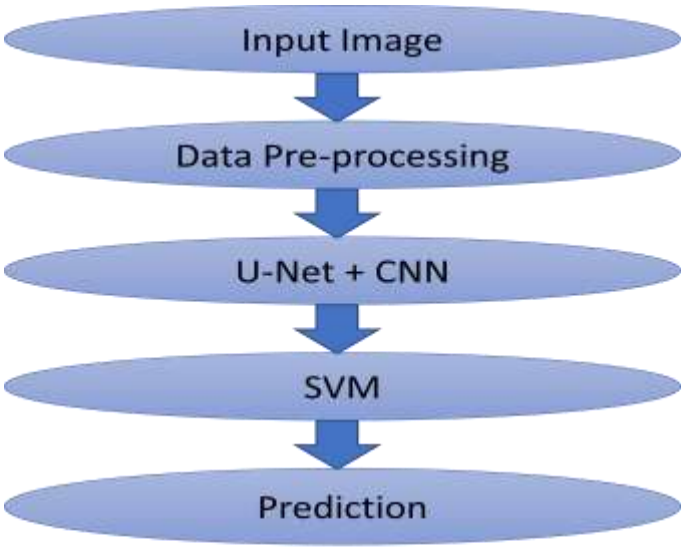

Figure 3: Data Flow Diagram of the Proposed Lung Cancer Detection Framework

5 Experimental Setup

The proposed model was implemented using Python and relevant deep learning libraries such as TensorFlow, Keras, and OpenCV. The experiments were conducted in a Jupyter Notebook environment, with model training performed both on local hardware (CPU) and optionally on cloud platforms like Google Colab utilizing GPU support (e.g., NVIDIA T4).

The U-Net architecture was used for segmenting lung regions from CT scan images. The model consists of an encoder-decoder structure with skip connections to preserve spatial features. Post-segmentation, a Convolutional Neural Network (CNN) was employed to extract spatial features from the segmented outputs. These features were then passed to a Support Vector Machine (SVM) classifier for binary classification into cancerous and non-cancerous categories.

The model was trained for 5 epochs with a batch size of 4 using the Adam optimizer and binary crossentropy as the loss function. EarlyStopping was applied to monitor validation loss and prevent overfitting. Hyperparameters such as learning rate, filter size, and dropout were manually tuned based on experimental performance.

For deployment, a Streamlit-based web application was developed, allowing users to upload CT scan images and receive real-time predictions. This serves as a practical demonstration of the model's usability in clinical or diagnostic environments.

6 Results and Evaluation

The proposed lung cancer detection system was evaluated using a validation set derived from the original dataset. The U-Net model effectively segmented lung regions from CT scans, while the CNN-SVM pipeline accurately classified cancer presence. Training curves demonstrated stable performance, with increasing accuracy and decreasing loss over epochs.

Figure 4 illustrates segmentation outputs, highlighting the U-Net's precision in isolating lung regions—crucial for improving classification reliability. The classification module achieved consistent results across training and validation sets, confirming the effectiveness of combining CNN feature extraction with SVM classification.

A Streamlit-based web application was also developed to demonstrate real-time usability. Users can upload CT images and receive immediate predictions. Figures 5 to 8 show key interface stages, including image upload, segmentation display, and prediction outputs such as "No Cancer Detected" or "Cancer Detected". This interactive platform highlights the system's potential for clinical integration.

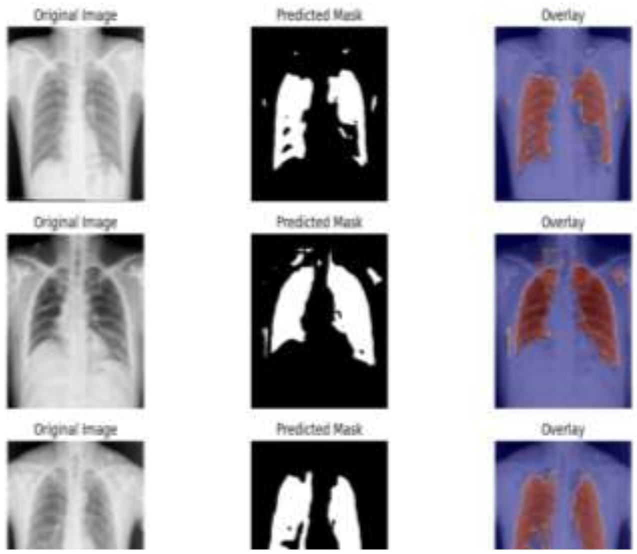

Figure 4: Segmentation Output Samples

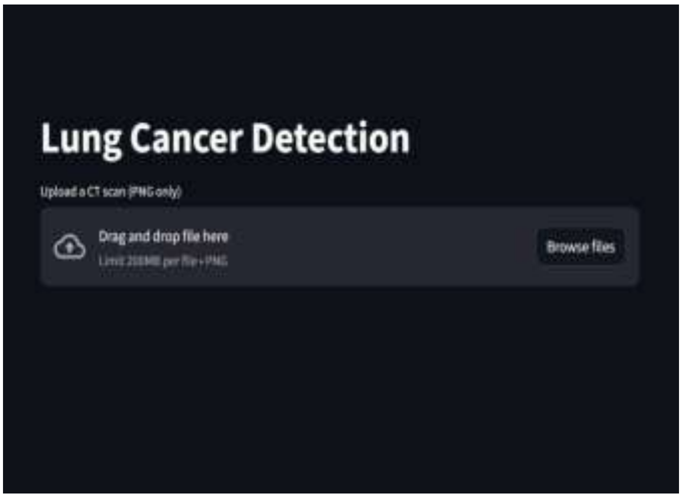

Figure 5: Streamlit App – Upload Interface

Figure 6: Streamlit App – Image Uploaded

Figure 7: Streamlit App – No Cancer Detected

Figure 8: Streamlit App – Cancer Detection Result

7 CONCLUSION AND FUTURE ENHANCEMENT

This research proposes an effective deep learning framework for automated lung cancer detection using CT scan images. The integration of U-Net for segmentation, CNN for feature extraction, and SVM for classification enables accurate identification of cancerous regions. The system demonstrated promising results in both segmentation accuracy and classification performance. Additionally, the development of a Streamlit-based application showcases the practical usability of the model in real-time diagnostic scenarios.

Future enhancements may include extending the model to multi-class classification for detecting cancer stages and incorporating ensemble learning to improve prediction robustness. Exploring advanced architectures like Liquid Neural Networks could offer better adaptability to dynamic data. Integration with clinical systems and expanding the dataset for training on diverse cases can further strengthen the model's real-world applicability in healthcare settings.

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