An Explainable Hybrid SVM–3D CNN Framework for Automated Lung Cancer Detection and Stage Estimation from CT Imaging

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Abstract: Lung cancer is a leading cause of cancer-related mortality worldwide, emphasizing the need for accurate and reliable Computer-Aided Diagnosis (CAD) systems. This study presents an enhanced CAD framework for lung cancer detection using CT images with unmarked nodules by integrating machine learning and deep learning techniques. A Support Vector Machine (SVM) is used to classify nodules as benign or malignant based on 2D features such as texture, shape, and intensity, while a 3D Convolutional Neural Network (3D CNN) analyzes volumetric CT data to capture spatial tumor characteristics and improve tumor assessment. To enhance clinical transparency, an Explainable AI (XAI) module highlights critical regions influencing predictions. The framework also includes cancer stage estimation and tumor burden analysis to assess disease severity based on nodule size, number, and distribution. Additionally, an automated report generation system provides structured clinical outputs. Experimental results demonstrate improved accuracy, interpretability, and decision support, making the framework a reliable and practical solution for lung cancer detection and analysis.

Keywords: *Lung Cancer Detection, Computed Tomography (CT), 3D Convolutional Neural Network (3D CNN), Support Vector Machine (SVM), Explainable Artificial Intelligence (XAI).*

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I. INTRODUCTION

Lung cancer is a leading cause of cancer-related deaths, mainly due to late diagnosis and the difficulty of detecting small pulmonary nodules in CT scans, as they often resemble normal anatomical structures and require radiologists to analyze numerous slices, making the process time-consuming and error-prone, which highlights the need for automated Computer-Aided Diagnosis (CAD) systems [1], [2]. Traditional CAD methods based on handcrafted feature extraction and Support Vector Machine (SVM) classifiers have shown limitations in handling complex medical image patterns [3], while deep learning models such as Convolutional Neural Networks (CNNs) have improved detection performance. However, many existing approaches rely on 2D analysis and fail to capture three-dimensional spatial information present in CT scans [4]. To address these limitations, this research proposes a hybrid SVM–3D CNN framework that enhances detection accuracy and reliability, with the integration of Explainable Artificial Intelligence (XAI) techniques to improve transparency and support clinical decision-making [5]. Early detection of lung cancer is essential for improving survival rates, as patients diagnosed at early stages have significantly better outcomes and can often be treated using less aggressive methods such as surgery. However, lung cancer is usually asymptomatic in its early stages, making small pulmonary nodules difficult to detect without systematic screening [6]. Low-dose CT scans are effective for identifying early lung abnormalities, but

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analyzing a large number of images can be time-consuming and prone to diagnostic errors. AI-based CAD systems, particularly those using CNN models, can assist by automatically detecting patterns in CT images, improving accuracy and enabling timely intervention [2], [4].

II. LITERATURE SURVEY

Early Computer-Aided Diagnosis (CAD) systems for lung cancer detection relied on handcrafted features such as texture, shape, and intensity, combined with machine learning algorithms like Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Decision Trees [1], [2]. Among these, SVM demonstrated strong performance for high-dimensional data and small datasets due to its robust decision boundaries [3]. However, these traditional approaches depend heavily on manual feature engineering and fail to capture complex spatial and structural patterns, leading to poor generalization [4]. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become prominent in medical imaging by automatically learning hierarchical features from CT scans, significantly improving detection accuracy [5]. Architectures such as VGG, ResNet, and DenseNet have been widely applied [6], yet most 2D CNNs are limited in capturing the full 3D structure of lung nodules. To address this, 3D CNNs have been introduced to process volumetric data, enhancing spatial representation and classification performance [5], [7]. Furthermore, hybrid approaches combining CNNs with traditional classifiers like SVM have shown improved accuracy and generalization capabilities [8]. In addition, Explainable AI (XAI) techniques such as Grad-CAM and LIME have been incorporated to improve transparency and trust in model predictions [9], [10].

Despite these advancements, several research gaps remain. Existing studies often lack effective integration of hybrid models with volumetric (3D) analysis, limiting their ability to fully exploit spatial features. Moreover, many models provide limited interpretability and fail to incorporate clinically meaningful outputs such as tumor staging and detailed analysis. Therefore, there is a need for a comprehensive framework that combines hybrid learning, 3D feature extraction, explainability, and clinical relevance to enhance the accuracy and usability of lung cancer detection systems.

III. PROPOSED SYSTEM

Detecting lung cancer from CT scans is challenging due to the small size, irregular shape, and low contrast of nodules that often resemble normal structures, making manual analysis time-consuming and dependent on radiologist expertise, which can lead to variability and missed detections, especially in early stages. The growing volume of imaging data further limits scalability. Although traditional CAD systems and deep learning models such as CNNs have improved detection, they often rely on handcrafted features or 2D analysis and lack interpretability. The literature highlights key gaps, including reliance on single-model approaches, limited use of 3D volumetric analysis, lack of clinically meaningful outputs such as cancer staging and tumor burden assessment, and minimal focus on explainable AI for transparency. To address these issues, this study proposes a Hybrid SVM–3D CNN framework that combines machine learning with deep volumetric learning to improve accuracy while incorporating explainability and clinically relevant outputs for more reliable and practical lung cancer diagnosis.

➢ *Lung Cancer Detection Algorithm (CT image / Diagnostic report)*

- Step 1: CT scan images are taken as input.
- Step 2: Images are preprocessed (normalization, noise removal, lung segmentation) and nodules are detected.
- Step 3: Features are extracted using 2D methods for SVM and 3D volumetric patches for 3D CNN
- Step 4: SVM and 3D CNN classify the nodules independently.
- Step 5: Outputs are combined using decision-level fusion to generate final classification (benign/malignant).
- Step 6: Stage estimation, tumor analysis, and Grad-CAM visualization are performed.
- Step 7: Final diagnostic report is generated.

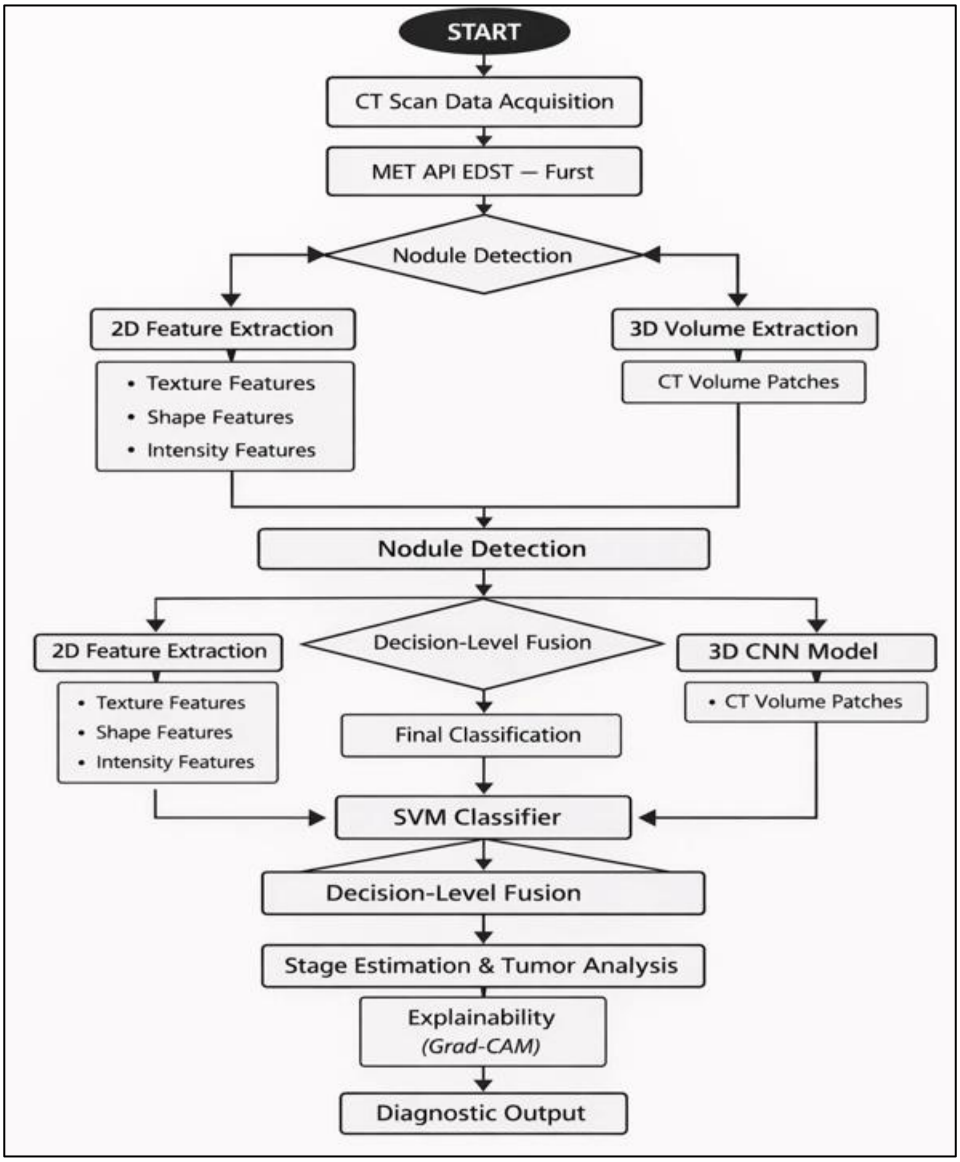

Fig. 1. Proposed System Flowchart for SVM - 3D CNN Framework

IV. SYSTEM METHODOLOGY

The methodology follows a quantitative, data-driven approach for lung cancer detection using CT scans, assuming malignant nodules show distinct features such as irregular shape, complex texture, and 3D spatial patterns. CT images provide high-resolution volumetric data, enabling effective feature extraction. The proposed Hybrid SVM–3D CNN framework includes four stages: data acquisition, preprocessing, feature extraction with model development, and multimodal fusion. The process involves image preprocessing, nodule detection, and analysis, ultimately producing accurate and clinically meaningful predictions.

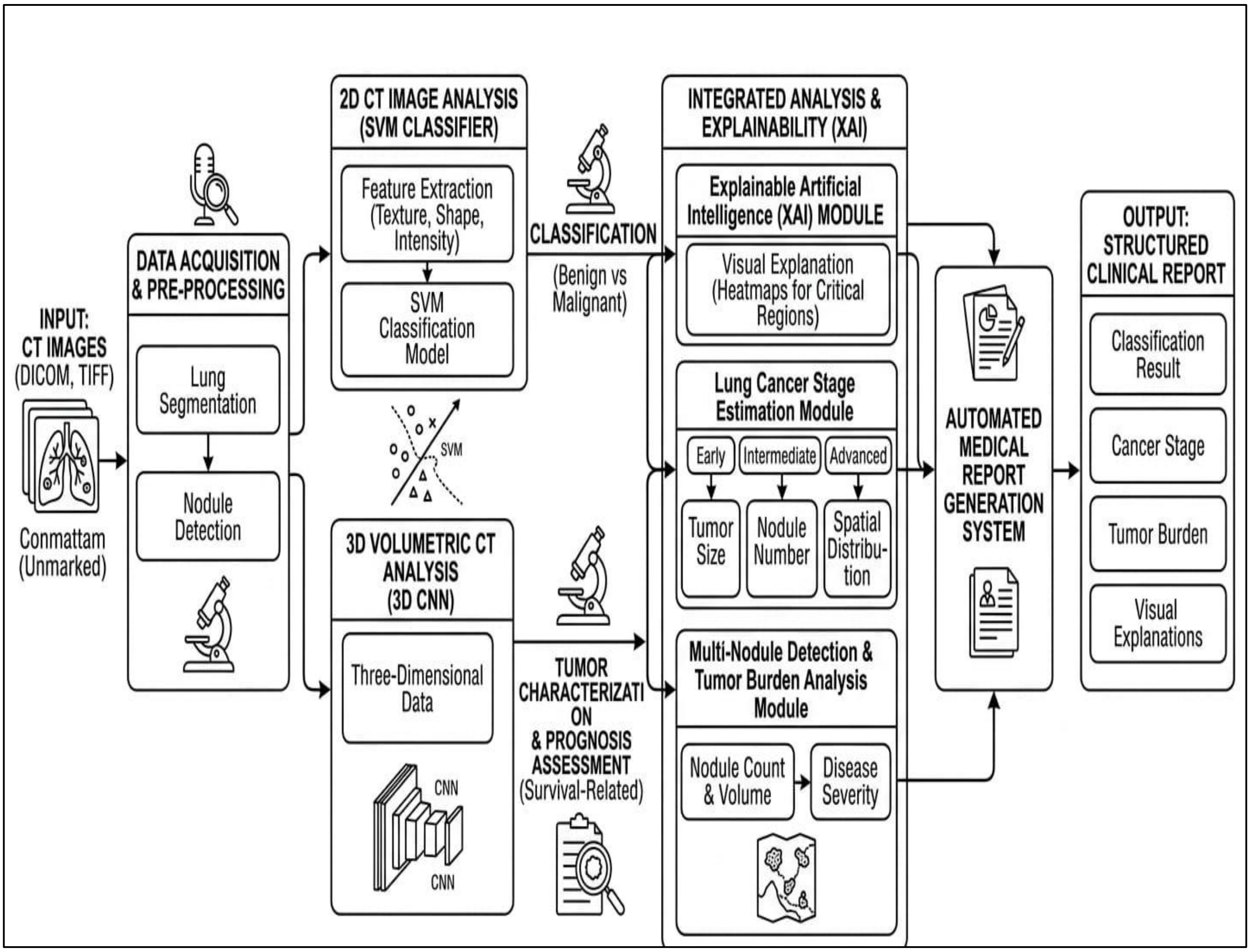

Fig. 2. Hybrid SVM-3DCNN Architecture for Lung Cancer Detection

➢ *Input Layers*

The input layer consists of CT scan images (DICOM/TIFF) forming a 3D lung structure. These images may contain noise and require preprocessing. Data quality is crucial, as it directly impacts feature extraction using SVM (2D) and 3D CNN, affecting overall detection accuracy.

➢ *2D Feature Extraction and SVM Modelling*

In the first branch, handcrafted 2D features (texture, shape, intensity, and edges) are extracted from lung nodules and fed into an SVM classifier, which learns an optimal decision boundary to distinguish benign and malignant cases, providing effective classification and good generalization, especially for smaller datasets.

➢ *3D Volumetric Feature Extraction and CNN Modelling*

In the second branch, a 3D CNN analyzes volumetric CT data to capture spatial continuity and tumor depth, enabling better detection than 2D methods. It learns features and outputs classification probabilities, which are fused with SVM results to produce final predictions along with stage estimation, tumor analysis, and Grad-CAM visualizations for improved interpretability.

V. RESULTS AND DISCUSSIONS

The Hybrid SVM–3DCNN framework outperforms standalone models by combining SVM's stable feature-based classification with 3D CNN's volumetric learning, achieving higher accuracy, precision, recall, F1-score, and ROC–AUC while significantly reducing false negatives.

Table 1. Performance of Individuals & Hybrid Models

Model	Modality	Accuracy (%)	Precision	Recall	F1-Score
SVM	2D Handcrafted Features	83.4	0.82	0.79	**0.80**
3D CNN	3D CT Volumetric Data	91.2	0.90	0.92	**0.91**
Hybrid (SVM + 3DCNN)	**2D + 3D Fusion**	**94.3**	**0.93**	**0.95**	**0.94**

The Support Vector Machine (SVM) classifier used handcrafted 2D features such as texture, shape, intensity, and edges. It achieved good accuracy and precision for clear cases but showed lower recall for small or irregular nodules, as handcrafted features cannot fully capture complex spatial and volumetric tumor patterns. The 3D CNN processes CT slices as volumetric data, capturing spatial depth and continuity to better detect complex tumors than 2D methods. It improves sensitivity, ROC–AUC, and reduces false negatives but requires regularization techniques like early stopping, normalization, and cross-validation to prevent overfitting and ensure stable performance.

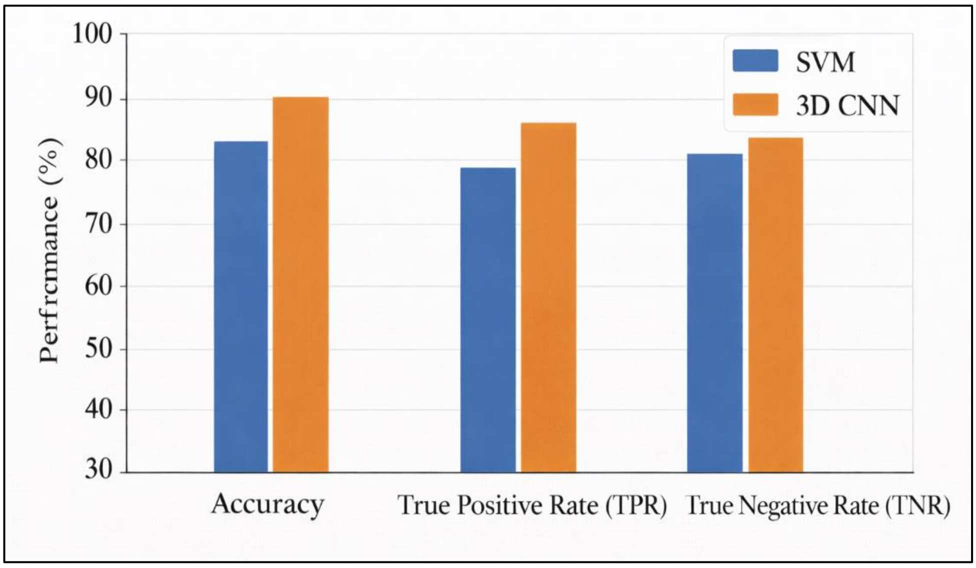

Fig. 3. Performance Comparison of SVM and 3DCNN Models

VI. CONCLUSION

This study presents a Hybrid SVM–3DCNN framework for lung cancer detection using CT scan images. The model combines handcrafted feature extraction (SVM) and volumetric learning (3D CNN) to capture structural and spatial characteristics of nodules. Results show improved accuracy, sensitivity, and reduced false negatives compared to standalone models. Decision-level fusion and XAI enhance interpretability and reliability. The system supports clinical decision-making and offers a scalable solution for early lung cancer detection.

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