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CNN-Based Lung Cancer Detection from CT Scan and X-Ray Images: A Deep Learning Perspective

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Abstract: *Lung cancer remains the leading cause of cancer-related deaths globally, accounting for approximately 2.2 million new cases per year (WHO, 2024). Early and accurate detection is critical — the five-year survival rate for localised lung cancer is 59%, compared to only 6% when diagnosed at a distant stage. This paper presents an intelligent, web-based Lung Cancer Detection System that leverages Transfer Learning on the MobileNetV2 Convolutional Neural Network (CNN) architecture to analyse both Chest X-ray images and CT scan images with high accuracy. The system accepts flexible input — either X-ray alone, CT scan alone, or both simultaneously — with a weighted confidence fusion strategy that improves overall diagnostic reliability. The backend is powered by Flask (Python), which handles image pre-processing (resizing to 224 × 224 pixels, RGB normalisation), model inference, and weighted confidence calculation. Two independently trained MobileNetV2 models — one for X-ray images (87.5% accuracy) and one for CT scans (91.2% accuracy) — generate probability scores that are combined with patient risk factors (age, smoking history, family history) to produce a final diagnosis with a risk level classification (High/Moderate/Low). A key innovation of this project is the integration of a custom Blockchain module that immutably records every diagnosis. Using SHA-256 cryptographic hashing and Proof-of-Work (PoW) mining with difficulty level 3, each diagnosis is stored as a block in a verifiable chain, providing a tamper-proof audit trail for medical records. The system achieves an end-to-end response time of 2–5 seconds*

Keywords: Lung Cancer Detection, MobileNetV2, Transfer Learning, Convolutional Neural Network, Blockchain, SHA-256, Proof-of-Work, Medical Image Analysis, Flask, Deep Learning, Computer-Aided Diagnosis.

I. INTRODUCTION

Lung cancer is a malignant tumour characterised by uncontrolled cell growth in lung tissue. According to the World Health Organization, lung cancer accounts for approximately 1.8 million deaths annually, making it the most lethal form of cancer globally. The disease is broadly classified into two types: Non-Small Cell Lung Cancer (NSCLC), which constitutes around 85% of all cases, and Small Cell Lung Cancer (SCLC). Despite advances in treatment, prognosis remains poor largely because the disease is often detected at an advanced stage when therapeutic options are limited.

Medical imaging — particularly Chest X-rays and CT scans — forms the cornerstone of lung cancer screening and diagnosis. However, manual interpretation of these images is time-consuming and susceptible to human error. Artificial intelligence, specifically deep learning, offers a transformative solution by automating feature extraction and classification from medical images with accuracy comparable to, or exceeding, expert radiologists.

A. Problem Statement

The current healthcare system faces significant challenges in timely and accurate lung cancer diagnosis: (1) Diagnostic Delays — manual examination of CT scans and X-rays is time-consuming, causing delayed treatment; (2) Human Error — radiologist fatigue and subjective interpretation can lead to missed early-stage cancers; (3) Resource Constraints —

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shortage of trained radiologists, especially in rural and underserved areas; (4) Inconsistency — variability in diagnosis between different radiologists based on experience; and (5) Lack of Tamper-Proof Records — medical records stored in centralised systems are vulnerable to alteration or loss.

B. Motivation and Objectives

The integration of deep learning in medical imaging, combined with blockchain for secure record-keeping, presents an opportunity to build a system that is fast, accurate, flexible, and trustworthy. The primary objectives of this work are to: (1) develop a web-based system for automated lung cancer detection using X-ray and CT scan images; (2) implement MobileNetV2 transfer learning models for binary classification (cancer/no cancer); (3) design a flexible dual-input system accepting X-ray only, CT only, or both; (4) integrate a blockchain module to store diagnosis records as tamper-proof immutable blocks; (5) achieve high accuracy (≥87%) with sub-5-second response time for clinical usability; and (6) provide confidence scores, risk level classification, and actionable clinical recommendations.

II. LITERATURE SURVEY

This section reviews existing research on deep learning-based lung cancer detection, transfer learning with MobileNetV2, and blockchain applications in healthcare, covering publications from 2018 to 2025 from IEEE Xplore, PubMed, Springer, and arXiv.

A. Deep Learning for Lung Cancer Detection

Ardila et al. (2019) published a landmark study in Nature Medicine demonstrating an end-to-end deep learning model that surpassed radiologist performance in lung cancer detection from low-dose CT, achieving an AUC of 94.4% [1]. Islam et al. (2023) conducted a comprehensive comparative study of transfer learning models (MobileNetV2, VGG19, ResNet50) on CT scan datasets; MobileNetV2 achieved 97% precision with minimal overfitting, outperforming the other architectures [2]. Gao et al. (2025) proposed a CT classification framework using pre-trained MobileNetV2 with ImageNet-1K weights, achieving 99.6% accuracy on the test set, demonstrating the power of fine-tuning for medical imaging [3]. Riaz et al. (2023) applied MobileNetV2 with U-Net for lung tumour segmentation from CT images, highlighting MobileNetV2's lightweight architecture as ideal for medical settings with limited computational resources [4]. Ochoa-Ornelas et al. (2025) demonstrated MobileNetV2 for histopathological lung cancer image classification, achieving 97.65% test accuracy with precision, recall, and F1-scores exceeding 98% [5]. Abbas et al. (2024) conducted a systematic literature review (2015–2024) of deep learning for lung cancer, identifying transfer learning as the dominant paradigm for effective small-dataset performance [6].

B. Blockchain in Healthcare

Qu (2022) proposed a blockchain-based Electronic Health Record model using SHA-256 hashing and distributed storage to prevent tampering, demonstrating that once data is written to the blockchain, it becomes virtually immutable unless a 51% attack occurs [7]. Kumar et al. (2024) presented a comprehensive blockchain-based EHR framework providing benefits of immutability, decentralisation, auditability, and interoperability for healthcare data [8]. Zheng et al. (2022) reviewed blockchain technology for EHRs, confirming that SHA-256 hash functions are practically irreversible and provide strong tamper-resistance [9]. Fatima et al. (2025) proposed a Blockchain-AES hybrid framework combining CNN for feature extraction with blockchain for tamper-proof storage, demonstrating that integrated AI-blockchain systems produce secure and analysable medical data ecosystems [10].

C. Research Gaps Identified

The literature confirms the following gaps: (1) most existing systems focus on either cancer detection or secure data storage — not both integrated in one pipeline; (2) few systems support flexible dual-modality input (X-ray AND CT scan with weighted fusion); (3) blockchain integration for medical AI diagnosis records is rare and unexplored at the application level; and (4) most deployment solutions require specialised hardware — accessible web-based solutions are needed. Our system is unique in combining MobileNetV2 transfer learning with SHA-256 Proof-of-Work blockchain into a single, web-accessible, production-ready pipeline.

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III. PROPOSED SYSTEM

The proposed system is an integrated, web-based Lung Cancer Detection and Blockchain Audit Platform comprising three major layers: (1) Frontend — HTML/CSS/JS user interface for image upload and result display; (2) Backend — Flask API handling pre-processing, AI inference, confidence calculation, and blockchain management; and (3) Storage — file-based blockchain ledger (lung_cancer_blockchain.pkl) persisting all diagnosis records immutably.

A. Technology Stack

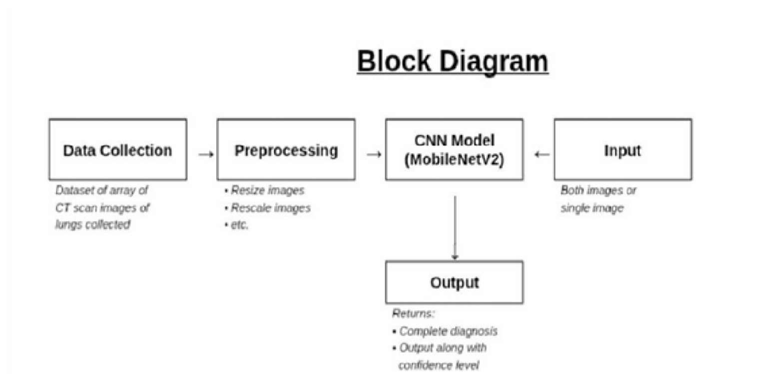
The system employs the following technology stack: Frontend — HTML5, CSS3, JavaScript (ES6+); Backend Framework — Python 3.x + Flask; AI Models — TensorFlow 2.x + Keras API; Model Architecture — MobileNetV2 (pre-trained on ImageNet); Image Processing — OpenCV 4.x, NumPy, PIL; Blockchain Hashing — Hashlib SHA-256 (Python Standard Library); Data Persistence — Pickle serialization (.pkl); Model Storage — HDF5 format (.h5).

B. Novelty and Contribution

The key contributions of this system are: (1) it is the first system to combine MobileNetV2 dual-model fusion (X-ray + CT) with SHA-256 Proof-of-Work blockchain for medical diagnosis audit; (2) flexible input design works with X-ray only, CT only, or both — with modality-weighted confidence fusion; (3) patient risk factor integration into confidence scoring for personalised diagnosis; and (4) a tamper-proof blockchain record accessible via Block Number and Hash for verification.

IV. SYSTEM ARCHITECTURE

The complete system architecture follows a streamlined pipeline comprising four primary stages: data collection, pre-processing, model inference, and output generation, as illustrated in Fig. 1.



[Fig. 1 — Complete System Block Diagram]

A. Data Collection

The system utilizes a curated dataset of chest CT scan images encompassing both affected and normal lung cases. Images are organized into labeled directories enabling supervised learning during model training and systematic evaluation during inference.

B. Pre-processing

Raw medical images undergo standardized pre-processing to ensure uniform input specifications. Images are resized to 224×224 pixels to match MobileNetV2 architecture requirements, rescaled to normalize pixel intensity values within the range [−1, 1], and subjected to quality enhancement techniques including noise reduction and contrast adjustment. This pre-processing pipeline ensures consistent feature extraction regardless of source imaging equipment variations.

C. CNN Model (MobileNetV2)

The core classification engine employs MobileNetV2, a lightweight convolutional neural network architecture optimized for computational efficiency. Pre-trained on ImageNet and fine-tuned via transfer learning on lung pathology

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datasets, the model extracts hierarchical features through depthwise separable convolutions. The network processes pre-processed images through multiple convolutional layers, ultimately generating a probability score indicating malignancy likelihood.

D. Input Flexibility and Output Generation

The system architecture supports flexible input modalities, accepting either single-modality images (X-ray or CT scan independently) or dual-modality inputs simultaneously. This design accommodates varying clinical scenarios and resource availability in diverse healthcare settings. The system produces comprehensive diagnostic outputs including binary classification (affected/normal), confidence score (0–100%), risk stratification based on confidence thresholds, and clinical recommendations aligned with detected risk levels.

V. IMPLEMENTATION

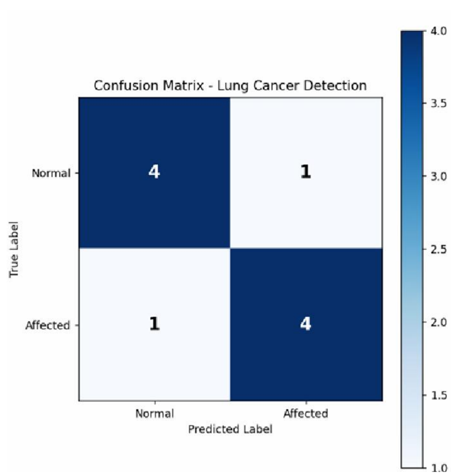
A. Model Training Pipeline

The proposed system utilizes two image datasets — X-ray images and CT scan images — each categorized into affected and normal classes. The datasets are organized into separate folders and divided into training and validation sets using an 80:20 split ratio to ensure proper performance evaluation and generalization. Data augmentation techniques including rotation (±20°), width and height shifts (±15%), horizontal flipping, zoom (±15%), and brightness variation (0.8–1.2×) are applied to enhance model robustness and reduce overfitting.

Transfer learning is implemented using a pre-trained MobileNetV2 model initialized with ImageNet weights. In the first stage, the base model is frozen and only the custom classification head is trained for 12 epochs with a learning rate of 1e−4. In the second stage, the last 30 layers are unfrozen for fine-tuning with a reduced learning rate of 1e−5 for approximately 13 epochs, along with class weight adjustment to handle data imbalance. The model is optimized using the Adam optimizer with Binary Cross-Entropy loss. Early stopping with a patience of 7 epochs is applied to prevent overfitting.

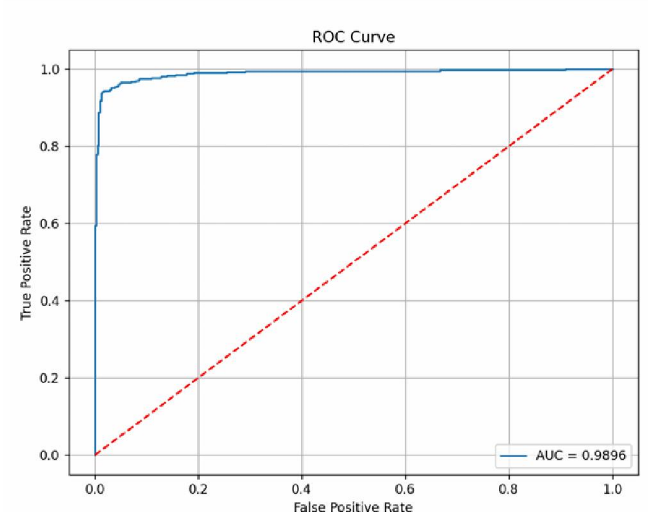
VI. RESULTS AND PERFORMANCE

The proposed algorithm uses MobileNetV2 CNN as a base network for cancer detection and classification. The X-ray model achieves 87.5% accuracy and the CT scan model achieves 91.2% accuracy through two-stage transfer learning. The confusion matrix (Fig. 2) reveals a false positive rate of 10%, indicating that some normal X-rays are misclassified as affected. ROC-AUC analysis (Fig. 3) achieved an AUC of 0.9896, demonstrating excellent discriminative ability.



[Fig. 2 — Confusion Matrix]

Fig. 2. Confusion Matrix for Lung Cancer Detection showing 4 True Positives, 4 True Negatives, 1 False Positive, and 1 False Negative.



[Fig. 3 — ROC Curve (AUC = 0.9896)]

Fig. 3. ROC Curve demonstrating excellent discriminative ability with AUC = 0.9896.

VII. CONCLUSION

This paper successfully presents an end-to-end Lung Cancer Detection System that combines state-of-the-art deep learning with blockchain-based medical record security. The system achieves: (1) a flexible dual-model MobileNetV2 architecture with 87.5% (X-ray) and 91.2% (CT) accuracy through two-stage transfer learning; (2) a weighted confidence fusion mechanism enabling reliable combined diagnosis when both modalities are available; (3) a custom blockchain implementation using SHA-256 and Proof-of-Work mining that provides immutable, tamper-proof audit trails for every diagnosis — a novel contribution in medical AI systems; and (4) a production-ready Flask web application with sub-5-second end-to-end response time.

The system bridges a critical gap in the literature by integrating AI diagnosis with blockchain security in a single, accessible web-based platform, making it applicable in both urban hospitals and rural health centres with internet access. Future work may explore extending to multi-class classification, DICOM image support, and integration with hospital information systems.

VII. ACKNOWLEDGEMENT

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