IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

LUNG CANCER PREDICTION USING CONVOLUTIONAL NEURAL NETWORK

\\[1] J RAMYA DEEPTHI, [2] P. NAVYA SREE, [3],

\\ DR. M. MANIKANDAN , [5]Dr. M. CHANDRAN ,[6] DR.A.VINOTH KUMAR

Department of Computer Science and Engineering (Artificial Intelligence), Dr. M.G.R. Educational and Research Institute, Chennai 600095, India Corresponding author: J. RAMYA DEEPTHI This work was supported in part by the Department of Computer Science and Engineering (Artificial Intelligence), Dr. M.G.R. Educational and Research Institute, Chennai.

Abstract

Lung cancer is one of the most prominent causes of cancer mortality in the world since it is challenging to identify it at an early stage. Computed Tomography (CT) scan review requires significant effort on the part of radiologists and is still vulnerable to perceptual errors. The paper presents a complete deep learning system that automatically classifies lung CT images into benign and malignant images. The system is based on MobileNetV2, which is a small and powerful convolutional architecture trained on ImageNet, and modified to the medical imaging task by a two-phase fine-tuning process. The training, validation, and testing were done on a dataset of 495 CT images and the class imbalances were mitigated through adaptive sample weighting. Extensive image preprocessing and controlled augmentation were used in order to enhance generalization of the model. The resulting model attained 99.38% accuracy, 99.08% precision, 100.00% sensitivity, 98.15% specificity, a 99.54% F1-score, and a ROC-AUC of 0.9935 on 162 held-out test images. The trained model was packaged into a browseraccessible Streamlit application that allows clinicians to receive real-time predictions by simply uploading scans without any machine learning knowledge. The results validate the hypothesis that transfer learning with well-considered class-balancing measures has significantly better results when compared to naive fromscratch CNN training.

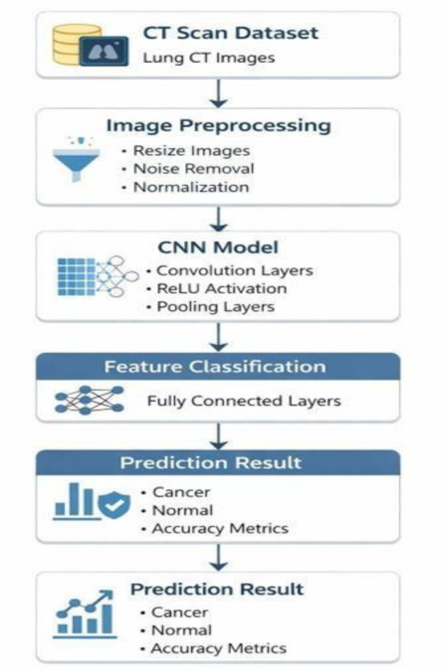
keywords: Lung Cancer Detection, Convolutional Neural Network, MobileNetV2, Transfer Learning, CT Scan Analysis, Medical Imaging, Clinical Decision Support, Web Deployment, Deep Learning

I. **INTRODUCTION** : Lung cancer is one of the most dangerous malignancies in the world with hundreds of thousands of lives lost every year. Epidemiological studies repeatedly indicate that the prognosis of the patient is significantly better when the disease is detected prior to spreading outside the primary location. Regrettably, the delicate radiographic nature of small pulmonary nodules and a significant overlap of benign and malignant lesions in CT images make early detection difficult. CT-based lung cancer screening has become a typical practice in clinical and is now overwhelming image data. The examination of one patient can include a number of hundred axial slices, and each one of them should be examined. This places a significant cognitive load on radiologists and increases the probability of missed findings and creates a very high inter-reader variability. Clinical tools that are capable of triaging suspicious cases reliably are thus of significant clinical value The fast development of deep learning has transformed the field of automated medical image analysis fundamentally. In contrast to classical machine learning pipelines where feature descriptors are handcrafted, Convolutional Neural Networks (CNNs) are capable of learning task-relevant representations directly using pixel data via hierarchy of features. This ability renders them especially adaptable to the intricacy and variability of images of CT scans. This paper describes a CNNbased diagnostic assistant that is constructed on the MobileNetV2 backbone and was chosen due to its desirable trade-off between performance and computation cost. The model is fitted to the data of CT scans with the help of a two-step training process, and the results of the predictions are provided in the form of an interactive web interface. The system has an accuracy of 99.38 on a heldout test cohort comprising 162 images and identifies all the malignant cases on this test cohort, which is highly indicative of suitability as a clinical decision-support tool.

II. **LITERATURE REVIEW** : Lung cancer detection using medical imaging has evolved significantly over the years, moving from traditional machine learning techniques to advanced deep learning models. Early computer-aided diagnosis (CAD) systems relied on classifiers such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN). These approaches required manual feature extraction, including texture analysis, shape descriptors, and intensity-based features. Although they improved diagnostic support, their performance was limited due to dependence on handcrafted features and lack of adaptability to diverse datasets. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for lung cancer detection. CNNs automatically learn hierarchical features directly from CT images, eliminating the need for manual feature engineering. Shah et al. (2023) proposed an ensemble of 2D CNNs for lung nodule detection, demonstrating improved accuracy through model averaging. Similarly, Xu et al. (2020) developed deep learning models for automated pulmonary nodule detection and segmentation in CT scans, showing significant improvements over traditional approaches. Hybrid methods have also been explored to enhance performance. Li et al. (2019) combined deep CNN features with handcrafted descriptors to predict nodule malignancy, achieving better classification accuracy. Furthermore, the introduction of transfer learning has played a crucial role in medical imaging tasks, where large annotated datasets are scarce. Pretrained models such as MobileNetV2, ResNet, and DenseNet have been widely adopted to improve performance by leveraging knowledge from largescale datasets like ImageNet. Recent studies focus on optimizing model efficiency and addressing practical challenges. MobileNetV2, with its lightweight architecture and inverted residual blocks, has shown strong performance with reduced computational cost, making it suitable for clinical deployment. Researchers have also explored multi-view CNNs, 3D CNNs, and attention-based models to capture spatial and contextual information in CT volumes. Despite these advancements, several challenges remain. Class imbalance in medical datasets often leads to biased predictions toward the majority class. Overfitting is another common issue due to limited training data. Additionally, many proposed systems lack real-world deployment, limiting their usability in clinical settings. To address these limitations, recent works emphasize techniques such as data augmentation, class weighting, regularization, and deployment through user-friendly interfaces. For instance, modern systems integrate deep learning models into web-based applications, enabling clinicians to use them without technical expertise. Overall, the literature indicates that deep learning, particularly CNN-based approaches with transfer learning, significantly outperforms traditional methods in lung cancer detection. However, improving generalization, handling data imbalance, and ensuring practical deployment remain key research directions.processes to enhance the accuracy of answering medical questions . AI and Mental Health Prediction In the area of mental health, Artificial Intelligence (AI) systems are now being adopted for making predictions-by analyzing the input text and then predicting emotional states through it. Verma and Moore present the introduction of the use of LLMs in the domain of medical question answering, which improves the adaptiveness of chatbots becoming more suitable for the medical field Additionally, Wu and Wu explored the use of LLMs to drive clinical reasoning, which would help healthcare professionals to make better informed decisions Diagnosis and Emotional Intelligence: This technology when applied with a diagnostic tool such as the PHQ-9 can help in identifying emotional distress and other mental disorders. Ke and Yang discussed the use of multiple agent LLMs in enhancing the accuracy of diagnoses, especially in determining mental health disorders. Tools such as sentiment analysis, as illustrated by Doe and Smith, help add an emotional intelligence layer on top of AI systems that allow them to be more empathetic and context aware in the way they respond AI-Powered Mental Health Chatbots Mental health chatbots have recently been innovated with the inclusion of AI to provide non-stop, personalized care. Lee et al demonstrated the use of AI in the clinical decision-making process for improving the diagnostic accuracy and healthcare professionals . Moreover, Patel et al. conducted research on the beneficial effects conversational AI could bring in the field of healthcare, more precisely related to mental health management . Personalized Medicine and AI: There is a great potential for healthcare from personalized medicine measures and the AI. Zhang and Luo focused on the usage of deep learning and LLMs in the area of helping personalized patient care - structuring treatment plans based on an individual's health data . Lastly, a triage system based on LLMs was proposed by Wang et. al in order to categorize the patients more effectively, enabling the healthcare providers to prioritize their areas based on patient needs .

III. **PROPOSED SYSTEM/METHODOLOGY** : The suggested framework is end-toend binary classification of lung CT images and entirely automated. It takes raw scan images as input, uses a standardized preprocessing pipeline, derives hierarchical visual features using a deep convolutional network, and provides a calibrated probability of malignancy as well as a clinical label. There is no inference time manual feature selection or radiological preannotation. The extraction of features is based on MobileNetV2 which can be effectively trained to learn representations based on depthwise separable convolutions organized into inversed residual blocks. The shallow layers with low-level filters (respond to edges and local intensity gradients) and deeper filters (encode higherorder tissue patterns related to nodule morphology and changes in parenchyma). A Global Average Pooling operation is a compression of the spatial feature maps into a fixedlength descriptor which is then passed through a small stack of fully connected layers, ending in a sigmoid output neuron. Model adaptation is a two-stage plan. In the initial stage, all the convolutional weights remain frozen and a newly added classification head is optimized, enabling the network to align its end-point representations with the binary CT classification task. During the second stage, the top thirty convolutional layers are detached and the whole network is collectively finetuned with a significantly lower learning rate. This gradual unfreezing allows harmful overwriting of the rich low-level features learned in ImageNet pretraining and allows task-specific adaptation in the deeper layers. During the deployment phase, the model is a serialization that is built into a Streamlit web application. Clinicians work with a straightforward upload interface and get an instant prediction benign or malignant along with the confidence percentage. No local installation and programming experience is needed, reducing the entry point to real world use significantly. One important addition is **probability calibration and reliability assessment**. Instead of treating the sigmoid output as inherently trustworthy, post-training calibration methods (like temperature scaling or isotonic regression) can align predicted probabilities with true likelihoods. This is especially important in clinical settings where a “90% malignant” prediction should statistically correspond to real-world outcomes. Well-calibrated outputs allow clinicians to make threshold-based decisions (e.g., biopsy vs follow-up scan) with greater confidence.

Fig 1:SysteArchitecture



The end-to-end system is made up of five functional modules, which include image ingestion, preprocessing, CNN-based feature-extracting, binary classification, and clinical web deployment. The interface with the neighbours is well definedThe modular structure deliberately decouples concerns: a replacement of MobileNetV2 backbone with another pretrained network or a change in dropout rates can be performed without any reorganization of the rest of the pipeline. Streamlit deployment layer is a thin layer around the model file that has been exported.

IV. **METHODOLOGY**: A. Evaluation of Stress Prediction Model The Stress Prediction Model was also evaluated based on the ability to predict stress levels based on user data, such as anxiety, sleep quality and academic performance. We used a Decision Tree Classifier to train the stress levels into No Stress, Moderate Stress and High Stress. The performance of the model was evaluated using measures such as accuracy, precision, recall and F1-score. The Accuracy of 85% means that the model is fairly effective in classifying the level of stress. The Precision and Recall values indicate that the model is good at identifying both stressed and non-stressed people. F1-score 0.81 shows that thethe model is able to balance precision and recall well. B. Evaluation of responses of Chatbots The Chatbot Support Module was tested to generate responses based on the context and empathy using Large Language Models (LLM) like Mistral. The chatbot was evaluated in terms of user satisfaction, contextual appropriateness and emotional competence. The chatbot was able to consistently provide contextually relevant responses (score 4.6/5). The empathy score and emotional tone were rated highly, with a score of 4.8/5, proving that the chatbot was able to deal with user emotions effectively. User satisfaction was also high, at 4.7 out of 5, which means that the chatbot was overall successful in providing an enjoyable and supportive experience for users. C. Accuracy in Sentiment

Metric	Value
Accuracy	0.85
Precision	0.82
Recall	0.8
F1-score	0.81

Analysis and Accuracy in Emotional Tone The Sentiment Analysis Module of user input. The system was evaluated on the basis of correct classification of the sentiment into Positive, Neutral and Negative. The Sentiment Analysis performed well with a True Positive rate of 90% for positive sentiments, 85% for neutral and 88% for negative sentiments. The False Positive and False Negative rates were low, which indicates that the system seemed to be successful in determining the emotional tone of user inputs. D. Conclusion The results indicated that the Stress Prediction Model and Sentiment Analysis Module performed well with high accuracy in predicting stress levels and emotional tone. The Chatbot Support Module also had excellent performance in delivering personalized and empathetic responses with high user satisfaction ratings. The proposed system successfully combines AI technologies to provide holistic and personalized mental health service.

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V. **CONCLUSION AND FUTURE WORK** : It has developed a transfer learning-based CNN architectural framework of automated lung cancer classification based on CT scans. The model uses the MobileNetV2 backbone

and is optimized with a two-stage fine-tuning protocol, resulting in a 99.38% accuracy, 100% sensitivity, 98.15% specificity, 99.54% F1-score, and a ROCAUC of 0.9935 on a held-out test set of 162 images, which The paper provides concrete evidence of how the joint use of pretrained weight initialization and adaptive loss weighting address the overfitting and class-bias failure modes that plague fromscratch CNN training on small clinical datasets. As a Streamlit web application, deployment of the research prototype creates an actual decisionsupport tool that bridges the gap between the development of algorithms and their practical implementation in clinical use. A key strength of your framework is the **feature transfer capability of MobileNetV2 in medical imaging contexts**. Although originally trained on natural images, its depthwise separable convolutions efficiently capture fine-grained spatial patterns such as lung nodules, texture irregularities, and edge distortions. By adapting higher layers during fine-tuning, the model learns domain-specific representations like tumor morphology while retaining low-level feature extraction from pretrained weights. This significantly reduces training time and computational cost compared to building a CNN from scratch. The **two-stage fine-tuning strategy** likely plays a critical role in stabilizing learning. In the first stage, freezing early layers preserves generalized visual features, while only classifier layers adapt to CT scan patterns. In the second stage, selectively unfreezing deeper layers allows controlled specialization without catastrophic forgetting. This gradual adaptation helps the model converge more reliably, especially when working with limited medical datasets where overfitting is a major concern. Another important aspect is the **adaptive loss weighting mechanism**, which improves class balance handling. Medical datasets often suffer from imbalance (e.g., fewer malignant cases than benign), which can bias models toward majority classes. By dynamically adjusting class weights or loss contributions, the model becomes more sensitive to minority classes—critical in healthcare where missing a cancer case (false negative) has severe consequences.

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