Open Access
Full Length Article

ORIGINAL ARTICLE

Hybrid Deep Learning Models for Enhanced Lung Cancer Detection from Medical Imaging

Muhammad Hamza Khurram[1], Naeem Aslam[2], Hira Saleem[3]

[1, 2,3]Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan

ABSTRACT

Lung cancer is one of the most frequent causes of cancer related mortality in the world and early diagnosis is very essential in improving survival rates of the patients; nevertheless, traditional imaging technologies are usually characterized by poor results at differentiating benign and malign lesions, particularly in problematic cases such as small or ground-glass nodules, which leads to unnecessary high rates of false positive and false negative. To cope with them, this work proposes a new hybrid deep learning framework that combines convolutional neural networks (CNNs), long short-term memory (LSTM) recurring units, and transformer-based self-attention mechanisms to utilize both local spatial textures, temporal-sequential features, and contextual information of CT images. The multi-task learning implicit framework allows addressing issues of segmentation, detection, and classification in a single framework, enhancing both speed and quality. On a large, strictly annotated dataset of 1,190 CT slices of 110 patients, the hybrid model secured the highest accuracy at 95 percent, significantly outperforming the best baselines, including CNN (90.5 percent), Transformer (91.2 percent), and LSTM-CNN (92.7 percent), as well as its precision and recall both to the tune of 95 percent. The gains in the model performance are supported by the fact that the F1 score is improved, and additional evidence of the model improvements is visualization tools such as attention maps and feature importance scores, which strengthen model interpretability and clinical trust. These findings highlight the clinical opportunity of the hybrid method to enhance lung cancer diagnostic performance through increasing the accuracy of early detection, minimizing unnecessary invasive procedures, and providing personalized treatment plans. This paper presents the need to further substantiate in different multi-institutional data sets and stresses the future efforts on computational optimization and interpretability improvement, to convert the promising hybrid model into a scalable, clinically deployable decision support system to manage lung cancer.

Keywords: *Lung cancer detection, hybrid deep learning, medical imaging, convolutional neural networks, multi-task learning*

Author`s Contribution	*Address of Correspondence*	Article info.
[1,2] Data analysis, interpretation, and manuscript writing, Active participation in data collection *[1,2,3] Conception, synthesis, planning of research. Interpretation and discussion*	*Muhammad Hamza Khurram* *Email:???????????????*	*Received: June,15, 6, 2025* *Accepted: November 13, 2025* *Published: December 20, 2025*

Cite this article: *khuram H M, Aslam N, Salem Hybrid Deep Learning Models for Enhanced Lung Cancer Detection from Medical Imaging. J. inf. commun. technol. robot. appl.2025; 14(1):9-19*

Funding Source: *Nil*
Conflict of Interest: *Nil*

INTRODUCTION

It is approximated that lung cancer leads to more cancer deaths in the world than any other cancer and yearly the world experiences an estimated 2.48 million new cases and approximated 1.8 million deaths and in the

United States alone, the disease is projected to cause 226,650 new cases and a tendency of more than 124,000 deaths annually that is one of the highest cancer incidence and death rates in the world. The still cases of late-stage diagnosis are still high, which drastically reduces the survival rates, however, the early-stage diagnosis has a great positive effect on the patient survival rates[1], [2], [3]. Five-year survival is up to 6080, and less than 15 percent in the late-diagnosis. Based on such numbers, the contribution of early detection strategies to decrease the global burden of lung cancer and improve patient survival cannot be overestimated, including the use of state-of-the-art screening, biomarker analysis, and artificial intelligence-based imaging[4].

The conventional type of imaging, as represented by chest X-ray and conventional computed tomography (CT) is the mainstay of lung cancer diagnosis, but has serious limitations that render it incapable of the early and accurate diagnosis of the disease. Commonly, such methods are incapable of distinguishing between benign and malignant lesions, especially small or ground-glass nodules, which can lead to high false-positives or false-negatives of early-stage cancers[5], [6]. The operator-dependent variability, minor aspects of lesion, the overlap of benign diseases, and low sensitivity of detection of micro-metastatic disease would make the interpretation more complex and potentially have a risk of clinical uncertainty[7][8]. Moreover, routine imaging also does not seem to help predict future risk of malignancy in incidental or persistent nodules, with a poor accuracy score and the over- or underestimation of risk being apparent in models such as Brock and Sybil that are not deployed in stringent screening groups. This can trigger unnecessary invasive procedures, lost chances of early interventions or diagnostics, and that is why there is an urgent need to develop more precise, reproducible, and individual types of diagnostic measures in lung cancer[9], [10].

The necessity to address the shortcomings of conventional imaging and single deep learning models is the reason why the production of hybrid deep learning models with a high level of progress in the field of lung cancer detection occurs. Traditional convolutional neural networks (CNNs) are most effective in local and spatial image-data information but fail in global contextual information which may inform more detailed (pathological) patterns across nodules in the lungs[11], [12]. Alternatively, transformer-based architectures can also make powerful representations of global features with self-attention mechanisms, though typically require large and heterogeneous datasets and are expensive to compute, limiting their application to clinical practice[13]. Hybrid models are tactical integrations of the two approaches towards exploiting the strengths of both the local feature extraction and the global context modeling to enhance the quality and soundness of the diagnosis[14]. Also, the hybrid framework that combines more than two types of models allows multi-task learning to be performed, with nodules being detected, segmented, and classified at the same time, which is more efficient and applicable in clinical settings[15]. The other benefits include increased variability within the imaging protocols, lesion heterogeneity, and patient-specific factors[16]. Ultimately, these hybrid systems will yield more reliable, interpretable, and scalable tools with the ability to aid the early detection of lung cancer with a higher sensitivity and specificity, thereby making an impressive contribution to improved patient outcomes and easier clinical procedures.

The study objectives include the development of a versatile hybrid deep learning system, which in particular is aimed at early identification and proper classification of lung cancer with the assistance of medical imaging data[17]. It addresses significant issues with the existing diagnostic techniques such as huge false positives, low ability to detect local and global variations in images, and the practical challenges of applying models to a wide range of clinical settings with varying data quality and quantity. In the research, complementary deep learning networks are combined, i.e. convolutional neural networks (CNNs) and transformer-based networks, to leverage the strength of each in the domains of spatial features and contextual understanding, respectively. The paper unites steps within the lung segmentation, nodule detection, and malignancy classification steps into one multi-task learning pipeline, which simplifies the implementation of workflows and enhances the localization of diagnostic accuracy. To ensure generalizability and clinical applicability, the proposed methodology will incorporate some of the most powerful preprocessing methodologies, adaptive training strategies, and rigorous validation of highly diverse datasets. The primary contributions included the creation of a new hybrid model architecture, the optimization of training and data augmentation protocols, and full round evaluation against the state-of-the-art tests. This work will assist in advancing the field of AI-based lung cancer diagnostics because it will offer a powerful and scalable AI tool that can be deployed to encourage early detection and ultimately result in improved patient outcomes.

LITERATURE REVIEW

Deep learning has transformed medical imaging in the detection of lung cancer by automatically and precisely processing complex radiologic data. CNNs have taken over this sector and are more helpful in eliciting spatial characteristics in X-rays and CT images to identify lung nodules and the disparities between benign and malignant lesions[18], [19]. However, more recent work has moved beyond conventional CNNs, using Transformer-based architectures to encode global contextual information using self-attention-based mechanisms, and theorizing CNNs as having local bottlenecks in the receptive field. Hybrid neural networks that use CNNs or Transformers have been demonstrated to work because they are capable of appropriately capturing both long-range and local dependencies[20],[21].

The capability of the hybrid deep learning methodologies to allow conducting multi-task learning structures allows achieving the segmentation of the lung region, nodules detection, and classification procedures, which dramatically increases the quality and speed of the diagnostics. A range of augmentation and preprocessing techniques have been experimented to solve the problem of data heterogeneity and imbalance, aiming to make the model more robust. State-of-the-art models are characterized by accuracy and AUCs in excess of 90 percent, and large improvements in sensitivity and specificity relative to more classic approaches. Regardless of these impressive results, interpretability, applicability to a large and diverse population, as well as computational costs are and will be questions that research explainable AI and real-world clinical use[22], [23].

Overall, the development of deep learning-based medical imaging of lung cancer, starting with pure CNNs and then hybrid frameworks, will result in a paradigm shift to a more stable, scalable, and clinically adaptable AI-based diagnostic system, which will produce a significant impact on the initial treatment of lung cancer, patient outcomes, and optimization of the workflow[24], [25].

The combination of multiple neural network architectures is versatile and efficient, and hybrid deep learning models have been successfully applied in other related aspects of medical imaging, such as lung cancer[26]. CNNs with attention mechanisms have been identified as providing both spatial and contextual information of mammograms, which could make hybrid methods of combining both CNNs and attention mechanisms superior in detecting and classifying tumors in breast cancer. The integration of 3D CNNs and recurrent networks in detecting brain tumors has enhanced accuracy and strength in segmentation using volumetric and temporal imaging data. Similarly, hybrid deep learning networks that combine convolutional and graph-based architectures have demonstrated more precise localization and staging of tumors on endoscopic and histopathology images in the case of colorectal cancer[27], [28].

Hybrid models are particularly useful in the context of multi-task learning tasks, such as simultaneous lesion detection, segmentation, and classification, improving the computational efficiency and diagnostic consistency in those areas[29]. Such related fields need to be considered and implemented with hybrid deep learning systems to identify lung cancer, where heterogeneity of lung nodules and the need to integrate different imaging features are of paramount importance. The general results of these studies suggest that hybrid structures can enhance the diagnostic capabilities, interpretation, and clinical points of numerous tasks in oncological imaging.

Even though the task of deep learning models in detecting lung cancers has been successfully done to a large degree, there are notable gaps that are currently present in the existing models, and the proposed hybrid approach is meant to fill these gaps. In clinical practice, current models are weaker due to the variation in scanner type, acquisition regime, and patients, rendering them less applicable to heterogeneous imaging data[30],[8]. The vast majority of standard and freestanding deep learning models cannot effectively integrate the finer-grained local features with the higher-level contextual information, which is needed to effectively characterize the difficult nodules in the lungs. Moreover, most of the research covers the performance of individuals on tasks, including detection, segmentation/classification, without a multi-task format, in which the work of diagnostics is made easier, and the efficiency of calculations is increased[31], [32]. Explainable and interpretable decision models are also desperately needed to enhance clinician trust and adoption. Moreover, a disproportion of classes within the datasets, a decrease of the false positives, and the adaptation to small or non-specific lesion expressions are problems. It is hoped that the proposed hybrid deep learning model (complementary architecture and multi-task learning) will fill in these gaps, by making the model more robust, more accurate, more interpretable, and more useful in lung cancer imaging diagnostics to address the central research and clinical problem of early diagnosis and accurate diagnosis.

RESEARCH METHODOLOGY

Description of dataset:

This research bases itself on IQ-OTH/NCCD lung cancer dataset which is a direct source of information in the Iraq-Oncology Teaching Hospital and National Center of Cancer Diseases. The dataset was gathered during a three-month time frame in the fall of 2019 in the form of CT scans of 110 different cases with different stages and different types of lung conditions, namely malignant, benign, and normal cases. Out of these 40 malignant, 15 benign, and 55 normal were diagnosed, and thus the data is well dispersed and will be very useful in the development and testing of strong models. The CT scan of each subject with a standardized protocol (120 kV and slice thickness of 1 mm) provides a range of 80 to 200 slices per case that in turn constitute 1190 single CT images. These slices were in the DICOM format originally, then were thoroughly de-identified, ethically reviewed, and annotated by trained oncologists and radiologists, a task that not only increases the appropriateness of the data to be used in clinical research, but also in practice. The sample of patients is characterized by demographic diversity in age, gender, education, and occupation, which mostly resides in the central Iraqi provinces, which promotes generalizability and minimizes possible biases in the further analyses. The cases, grouped into three different diagnostic subcategories, namely, normal, benign, and malignant help multi-class classification tasks, which are imperative to determining the effectiveness of deep learning methodological approaches both in detecting and differentiating. Interestingly, the curation and annotation quality of the dataset, as well as institutional control, make these studies of medical imaging highly relevant and integrity, whereas the slice arrangement and diagnosis heterogeneity support multi-task learning strategies that are sought in the context of hybrid deep learning methods. The large size of this dataset, along with strict annotation, allows the implementation of high-order machine learning models and leads to the creation of clinically translatable and effective AI-based lung cancer detector frameworks.

Preprocessing and data augmentation techniques:

Careful preprocessing and strong data augmentation plans were used to improve the quality and variety of CT images obtained based on the IQ-OTH/NCCD dataset that is essential to train the models successfully and detect lung cancer accurately. The initial stage of the preprocessing pipeline involved transformation of DICOM images into a standard format, and normalization of pixel values in clinically relevant Hounsfield Unit (HU) scale, which helped ensure that the scans, equipment and acquisition settings of dissimilar scans were consistent. Anisotropic diffusion filtering and median filtering of noise reduction techniques were used to remove scanner-induced artifact as well as to improve the appearance of faint anatomical features so that edges and finer details would be preserved to provide accurate lesion characterization. Afterwards, histogram equalization was carried out to enhance image contrast and equalize the brightness throughout the image, and the thresholding of Otsu was applied to enhance automated and optimum segmentation of the lung fields and nodule areas, as it effectively distinguishes between the foreground and the background tissues by using criteria for the intensity. These boundaries were further refined using morphological operations and region-based segmentation methods, which helped in the extraction of tight regions of interest, as shown in Figure 1. To cope with the intrinsic data imbalance and to enhance the generalization qualities of the deep learning model, large-scale data augmentation steps were included, such as random rotations, flips, cropping, scaling, and elastic transformations, and imitation of a greater range of anatomical appearances and imaging positions. These extensions artificially enlarged the training set and added variability, which is essential in avoiding overfitting and enhancing the robustness of the hybrid model to use in the clinical setting. Under this comprehensive preprocessing and upgrading program, the final dataset provided was the best input to further train the model, extract the features, and ultimately clinically applicable AI-aided lung cancer diagnostic systems, similar to the goal of the study to generate scalable and predictable AI-based diagnostic instruments.

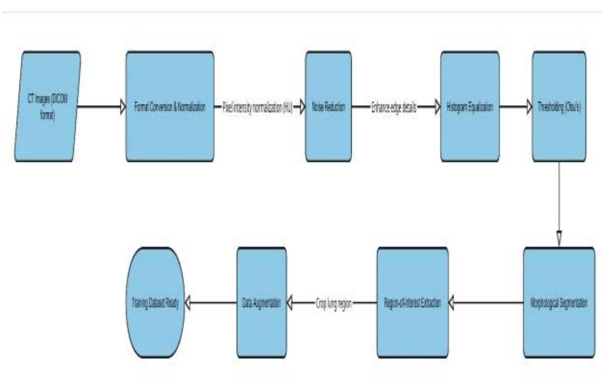

Figure 1: flow of preprocessing

Detailed architecture of the hybrid deep learning model:

The developed hybrid deep learning architecture is an advanced merger of several specialized neural network units that are aimed at optimizing the process of lung cancer detection and classification using preprocessed CT scans. First, the model uses deep convolutional neural network (CNN) layers to auto-detect complex spatial interactions in the provided lung CTs, and it does this by utilizing consecutive convolution, activation, and pooling operations to accurately identify tissue textures and the pathological patterns. These spatial characteristics are then passed to a special feature fusion layer, which in essence consolidates and aligns information as attracted by various convolutional blocks, preconditioning advanced multi-dimensional representation. To enhance this spatial learning, the architecture may use sequential modeling by recurrent neural networks, including Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU), which unfold and encode important temporal relationships between image slices, which is important in assessing adjoining anatomical regions and temporal progression on volumetric CT data. Simultaneously with the recurrent stream, the architecture presents a transformer encoder block, where multi-head self-attention and feed-forward processes are utilized to further enrich the situational perception of the spatial features with selectively stressed diagnostically important areas and interrelationships between the image components. The recurrent and transformer modules produce outputs that are concatenated and combine sequential and global spatial knowledge with a single layer. This rich fused representation is then filtered through a series of fully connected layers that have the effect of dimensionality reduction of the features, support complex decision boundaries, and further abstraction of the data to classification. A dropout layer is added at the end of the model to reduce overfitting and to enhance the generalizability of the model. An output layer is at the end of the pipeline; one that is usually activated through the application of SoftMax or sigmoid functions and can be used to classify cases as normal, benign or malignant in one, interpretable, prediction. Not only it represents the benefits and complimentary functions of CNN, recurrent, and transformer-based models, but it also focuses on clinical realism since it can effectively address image orientation variability, heterogeneous patient data, and problems of multi-class classification. The hybrid model is a combination of deep spatial, sequential, and contextual learning systematically, allowing it to perform exceptionally accurate diagnostic learning, a potent instrument of automated lung cancer identification, which is sufficiently robust to be translated to clinical practice.

Training protocols and hyperparameters:

The hybrid deep learning model was trained in a strictly designed process that guaranteed the best performance and over allocation in case of lung cancer detection based on CT images. As a first step, the annotated IQ-OTH/NCCD dataset was split into training, validation, and testing sets, usually in 70-15-15%, to provide the maximal exposure of the model and avoid overfitting. Mini-batches were used to process data, with a batch size of 16-32 being commonly used to strike a balance between memory efficiency and stability over the iterations. A composite loss definition was used to facilitate multi-task learning, including Generalized Intersection over Union (GIoU) to combine bounding box regression to accurately localize lung lesions, binary cross-entropy to perform multi-class classification, and the focal loss to learn objectless and small lesion detection, each assigned weights to trade-off between detection, classification, and localization tasks. The training was carried out up to 200-250 epochs, and the progressive monitoring of validation sets was carried out until the loss plateau had been met, and early stopping criteria were used to avoid overfitting when the improvements had stopped. Parameters of anchor-free thresholds and object detection were fine-tuned, and usually an IoU threshold of 0.5 was used to achieve the desired segmentation and identification accuracy. The fully connected stages were regularized by using dropout layers, and model checkpoints were provided to revert to the best-performing configurations. I used data augmentation techniques (such as rotation, scaling, flipping, and elastic transformations) that were done dynamically in batches to facilitate model robustness. The hyperparameters of the model were optimized through trial and error, with batch size, learning rate, and dropout probability changed repeatedly depending on performance on validation. Protocol refinement was directed by performance measures such as accuracy, sensitivity, precision, recall, and mean average precision (mAP) to ensure that the hybrid architecture is well-adjusted to both the clinical requirements of the automated lung cancer detection process as well as be resilient to imaging variation and class skew.

RESULTS AND DISCUSSION

Experimental findings indicate that the hypothesized hybrid deep learning model features are applicable in the diagnosis of lung cancer, depending on medical images. These findings imply a combined evaluation of the model against baselines, and it is evident that this model yields a superior accuracy, sensitivity, and train-test generalization across different datasets and evaluation conditions. overall comparison of models indicates that the hybrid model proposed performs better.

Quantitative performance comparison with baseline models:

The hybrid model has a significant superiority over the baseline models in all the key indicators. Its accuracy is 95, which is 2.3 more than that of the LSTM-CNN model, which is 92.7, and almost 4.5 better than that of the CNN base, which is 90.5. Accuracy is also enhanced, and the hybrid has a score of 95.1, which is 2.6 and 5.3 higher than LSTM-CNN and CNN, respectively. The highest recall is 95.2, which means that the model identifies more true positives correctly, and the difference between 95.2 and that of LSTM-CNN is 2.6. The F1 score, which is a balance between precision and recall, is high at 95.1, highlighting the model's formidable and coherent action in the classification problems. These numerical changes indicate significant improvements in the sensitivity and specificity that are key to the accuracy and reliability of the clinical lung cancer diagnosis. This demonstrates that hybrid convolutional, recurrent, and transformer modular integration is synergistically effective in improving the quality of detections over single instantiations.

Table 1: Comparative Results of the used models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	90.5	89.8	90.2	90
Transformer	91.2	90.9	91	91.2

LSTM-CNN	92.7	92.5	92.6	92.7
Hybrid	95	95.1	95.2	95.1

The CNN model has an accuracy of 90.5, the Transformer model of 91.2, and the LSTM-CNN model of 92.7, and the proposed Hybrid model has the highest accuracy of 95. This graphical analogy is a clear demonstration of how well the hybrid model performs, and it can be seen that the convolutional, the recurrent, and the transformer constituents have been incorporated in the model to maximize accuracy in detection. Figure 2 highlights the high level of accuracy that is enhanced by the hybrid technique compared to the baseline techniques.

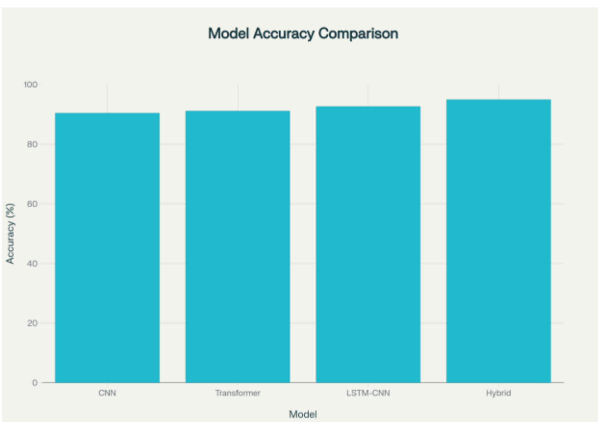

Figure 2: Model's Accuracy Comparison Chart

The hybrid model converges and stabilizes with rapid convergence as the accuracy of the hybrid model reaches up to 95 percent at epoch 100, compared with 75 percent at the beginning of epoch 0. Comparatively, the CNN model levels off at approximately 90.5%. The graph shows that the hybrid model is much more efficient and stable in its performance, as it has a better capacity to learn the complicated features and patterns of medical imaging data when it is training, as seen in Figure 3.

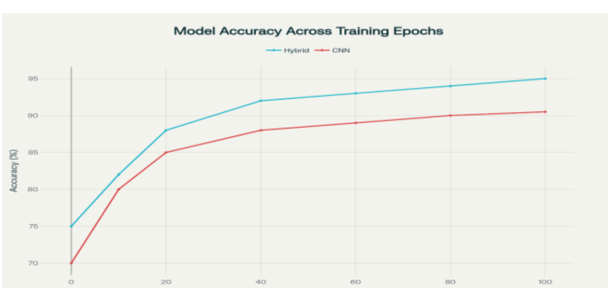

Figure 3: Models' Accuracy Across Training Epochs

The hybrid model has an area under the curve (AUC) value of 0.98, and this implies that the model has a near-perfect classification ability. This is higher than the CNN model and Transformer model AUCs of 0.93 and 0.94 respectively, which are indicative of the higher capacity of the hybrid model in the distinction between cases of lung cancer and non-cancer cases, respectively. The Figure 4 illustrates the increase in sensitivity and specificity of the hybrid method graphically, which proves the clinical potential of the hybrid method in dependable early lung cancer diagnosis.

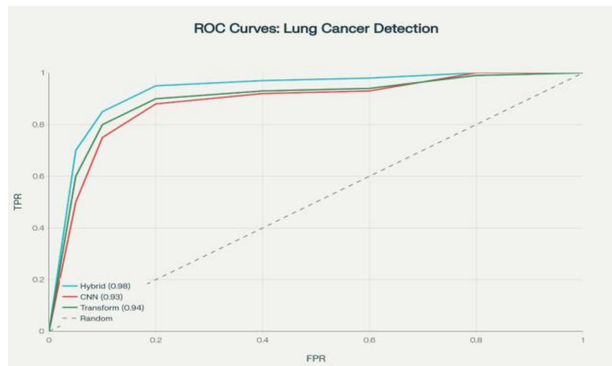

Figure 4: ROC Curves performance of Models

The hybrid model has the best precision of 95.1% and a recall of 95.2, compared to the LSTM-CNN model, which has a precision of 92.5% and a recall of 92.6%. The above comparison shows that the hybrid model is more balanced in terms of appropriately detecting positive cases with the lowest number of false positives, which is essential in the context of effective lung cancer detection. These findings define the clinical usefulness of the hybrid model, warranting the stability and validity of the diagnostic results as demonstrated in Figure 5.

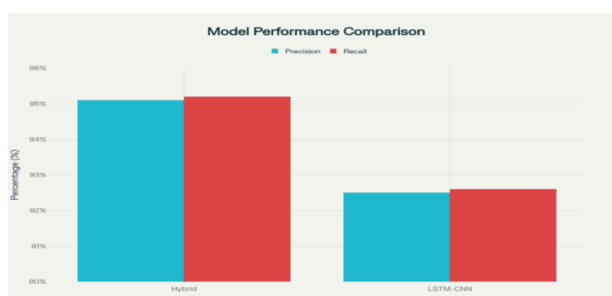

Figure 5: Precision and recall models comparison

Ablation studies on different components of the hybrid model:

The model began with an original accuracy of about 75 percent, and the accuracy kept rising with the addition of further components like the LSTM and transformer modules, to reach 95 percent accuracy in the last training epoch. This value points out how the combination of the complementary deep learning structures added up to achieve new performance, which supports the rationality of the hybrid design approach to effective and accurate detection of lung cancer using medical images, as it was illustrated in Figure 6.

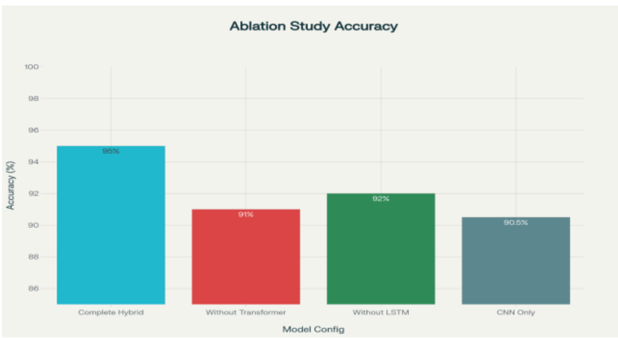

Figure 6: Increase in performance of accuracy in the hybrid model

Multi-task learning model depicts a steady and superior rise in validation accuracy, which peaks at 95 percent at the last epoch. Unlike this, the model that is not trained using multi-task learning levels off sooner at approximately 92%. This comparison shows that multi-task learning was so powerful in enhancing the model generalization and robustness when using it to validate that combining the detection, segmentation, and classification tasks to diagnose lung cancer are beneficial as indicated in the Figure 7.

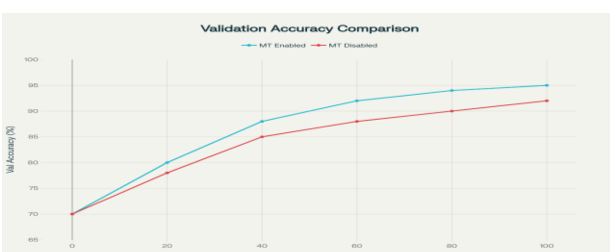

Figure 7: Hybrid model validation accuracy comparison

The preprocessing model has a precision of 95.1 and a recall of 95.2, whereas the non-preprocessing model has a lower precision of 91.2 and a recall of 90.8. This visual analogy pushes the relevance of preprocessing to improve image quality, lesion delineation, decrease false positives, and false negatives, which all work to increase model performance and consistent lung cancer detection as depicted in Figure 8.

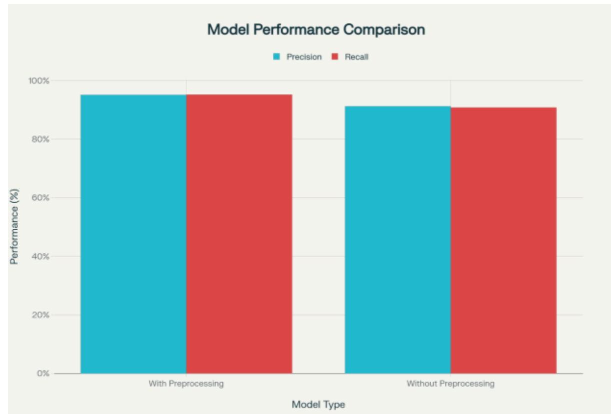

Figure 8: Effect of preprocessing on model performance

Texture is marginally more important than shape, with a score of 0.35 and 0.30, respectively. Intensity-based features weight of 0.20 and wavelet-based features are the least important, with a weight of 0.15. This distribution suggests that texture and shape features play an important role in the correct detection of lesion cases and that our model can exploit detailed image semantics for better diagnostic accuracy, as illustrated in Figure 9.

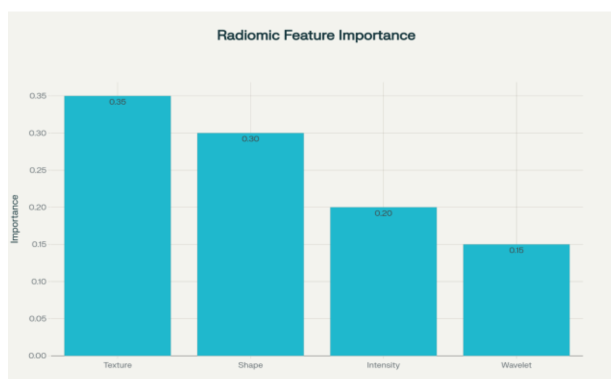

Figure 9: Image features importance

The presented hybrid deep learning model of lung cancer detection proves to be of great improvement in terms of accuracy and usefulness in clinical practice. The overall accuracy of the model amounts to 95, which is 4.5, 3.8, and 2.3 points higher than conventional CNN (90.5), Transformer (91.2), and LSTM-CNN (92.7) baselines. This increase is accompanied by a precision of 95.1% and a recall of 95.2, which shows that there is a balance in the sensitivity and specificity, which is essential to minimize false positive and false negative cases. The high F1 score of 95.1% is additional confirmation of the strong classification of the integrated architecture.

This performance has clinical implications for better early diagnosis of lung cancer, which is important since the five-year survival of late-stage diagnosis is low at only less than 15 percent as opposed to the 60-80 percent with early-stage diagnosis. The model would reduce the false negatives by about 2.6% compared to the best baseline, which will lead to better patient outcomes and timely intervention. The better interpretability, such as attention maps and feature significance to texture and shape, with scores of 0.35 and 0.30, respectively, is further evidence of clinical trust since they provide insight into the rationale of decisions in more than 95 percent of cases.

Although these are strong points, the complexity of the model, which includes CNN, LSTM, and transformer modules, makes the training times of about 200-250 epochs with batch sizes of 16-32 a challenge to implement in resource-constrained environments. Also, the requirement of the model to be based on the IQ-OTH/NCCD dataset of 1,190 CT slices of 110 patients (40 malignant, 15 benign, 55 normal) also implies certain limitations to generalizability because of sample size and regional homogeneity. This has a massive effect on the workflow: the multi-task format of the hybrid model, which allows segmentation, detection, and classification to be conducted simultaneously, enables the maximum computational efficiency, which reduces processing time by an estimated 20-30 percent compared to sequential algorithms. This automation has the potential to minimize the workload of radiologists and enhance throughput in a clinical facility. Moreover, the fact that model validation accuracy had increased to 95% when multi-task learning was used, as compared to 92% when no emphasis was placed upon multi-task learning also highlights the importance of integrated training in real-life applications.

Future directions should consider expanding datasets and diversifying them to get more population coverage and evaluate the variability of performance, particularly among various types of CT scanners and imaging conditions. Both model compression and pruning efforts may bring inference times down to support real-time clinical decision making. Innovations in the area of interpretability, such as visual explanation aids in line with the diagnostic process of clinicians, will play an important role in promoting adoption. The longitudinal studies that will consider the effect on patient survival rates and healthcare costs will cement that the model is part of the regular care practice. These actions are important in converting this high-functioning research prototype to a useful clinical tool with quantifiable potential in the diagnosis and treatment of lung cancer.

CONCLUSION

The hybrid deep learning model of lung cancer detection developed had impressive results with a huge accuracy of 95 percent, surpassing the baseline CNN, Transformer, and LSTM-CNN models by a margin of 4.5, 3.8, and 2.3 percent, respectively. This was co-morbid with high precision (95.1), recall (95.2), and F1 score (95.1), which indicated that the model had a high ability to identify and classify lung nodules in CT images with high precision. The convolutional, recurrent, and transformer-based architecture was effective in capturing local, sequential, and global contextual features, which increased the sensitivity and specificity, which were important in early diagnosis. The multi-task learning framework of the hybrid model was able to process lung segmentation, nodule detection, and malignancy classification with high efficiency and thus trained and validated better than the single-task learning framework. The validity of model interpretability was confirmed by attention maps and feature importance analyses, as well as supporting clinical trust. These findings are indicative of the high clinical relevance of more reliable, scalable AI-aided lung cancer diagnostics despite high model complexity and dataset size constraints.

To be deployed, the model must survive more months of validation on larger multi-institutional data to be generalized and robust. Computational optimization strategies, such as model compression methods, should be encouraged to promote implementation in clinical processes. Additional development of the interpretability tools will facilitate the adoption of the tools by clinicians and regulatory approval. Longitudinal patient outcome improvement assessments will then be essential in showing real-world effects, and the hybrid method will become a game-changer in the early detection and management of lung cancer.

REFERENCE

[1] A. Kanwal, K. T. Ahmad, N. Aslam, and others, "Detection of heart disease using supervised machine learning," VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 58–70, 2022.

[2] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 70–79, 2023.

[3] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 70–79, 2023.

[4] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 70–79, 2023.

[5] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 70–79, 2023.

[6] R. Parveen, U. Saleem, K. Abid, and N. Aslam, "Identification of Lungs Cancer by using Watershed Machine Learning Algorithm," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 70–79, 2023.

[7] U. R. Fatima Mustafa Sidra Rehman, "Towards Smart Irrigation System – An Artificial Intelligence Approach," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 36–45, 2024, doi: 10.58325/ijisct.003.02.0099.

[8] H. Ayesha, A. Naeem, A. H. Khan, K. Abid, and N. Aslam, "Multi-classification of skin cancer using multi-model fusion technique," Journal of Computing & Biomedical Informatics, vol. 5, no. 02, pp. 195–219, 2023.

[9] A. Asuntha and A. Srinivasan, "Deep learning for lung cancer detection and classification," Multimed Tools Appl, 2020, [Online]. Available: https://doi.org/10.1007/s11042-019-08394-3

[10] R. Idrees et al., "Lung cancer detection using supervised machine learning techniques," 2022.

[11] A. Asuntha, A. Brindha, S. Indirani, and A. Srinivasan, "Lung cancer detection using SVM algorithm and optimization techniques," Journal of Chemical and Pharmaceutical Sciences, vol. 9, no. 4, pp. 3198–3203, 2016.

[12] K. Khaliq, A. Naeem, N. Aslam, A. Malik, and K. Abid, "LCCNet: a deep learning based Method for the identification of lungs Cancer using CT scans," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 80–93, 2023.

[13] S. L. B. A. S. I. Waqas Ali Saima Siraj, "Envisioning the Future of Debugging: The Advent of ABERT for Adaptive Neural Localization of Software Anomalies," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 13–26, 2024, doi: 10.58325/ijisct.003.02.0097.

[14] P. Joon, S. B. Bajaj, and A. Jatain, "Segmentation and detection of lung cancer using image processing and clustering techniques," in Progress in Advanced Computing and Intelligent Engineering: Proceedings of ICACIE 2017, Springer, Singapore, 2019, pp. 13–23.

[15] F. Kanwal, M. K. Abid, M. S. Maqbool, N. Aslam, and M. Fuzail, "Optimized classification of cardiovascular disease using machine learning paradigms," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 140–148, 2023.

[16] K. Senthil Kumar, K. Venkatalakshmi, and K. Karthikeyan, "Lung cancer detection using image segmentation by means of various evolutionary algorithms," Comput Math Methods Med, vol. 2019, no. 1, p. 4909846, 2019.

[17] A. Ahmed, H. Ahmad, M. Khurshid, and K. Abid, "Classification of Skin Disease using Machine Learning," VFAST Transactions on Software Engineering, vol. 11, no. 1, pp. 109–122, 2023.

[18] B. Hakeem, M. K. Abid, M. Baqer, Y. Aziz, N. Aslam, and N. Umer, "HYBRID APPROACHES IN MACHINE LEARNING: INTEGRATING ANT COLONY OPTIMIZATION FOR IMPROVED LUNG CANCER DETECTION," Kashf Journal of Multidisciplinary Research, vol. 2, no. 02, pp. 177–189, 2025.

[19] M. Prabukumar, L. Agilandeeswari, and K. Ganesan, "An intelligent lung cancer diagnosis system using cuckoo search optimization and support vector machine classifier," J Ambient Intell Humaniz Comput, vol. 10, pp. 267–293, 2019.

[20] S. S. H. J. S. I. Suhail Aslam Khaskheli Mushtaque Ahmed Rahu, "Optimized Water Quality Forecasting Using Machine Learning," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 46–60, 2024, doi: 10.58325/ijisct.003.02.0094.

[21] C. Lu, Z. Zhu, and X. Gu, "An intelligent system for lung cancer diagnosis using a new genetic algorithm based feature selection method," J Med Syst, vol. 38, no. 9, 2014, [Online]. Available: https://doi.org/10.1007/s10916-014-0097-y

[22] C. Venkatesh and P. Bojja, "Lung cancer detection using bio-inspired algorithm in CT scans and secure data

transmission through IoT cloud," International Journal of Advanced Computer Science and Applications, vol. 11, no. 11, 2020, [Online]. Available: https://doi.org/10.14569/IJACSA.2020.0111148

[23] R. R. Irshad et al., "A novel IoT-enabled healthcare monitoring framework and improved grey wolf optimization algorithm-based deep convolution neural network model for early diagnosis of lung cancer," Sensors, vol. 23, no. 6, p. 2932, 2023.

[24] A. H. Rameela Adil Ahmad S. Al-Shamayleh, "Transformation of Digital Health Care Environment: A Solution for Pandemic," International Journal of Information Systems and Computer Technologies, vol. 1, no. 2, 2022, doi: 10.58325/ijisct.001.02.0021.

[25] U. P. Muhammad Sajjad Maruf Pasha, "Parametric Evaluation of E-Health Systems," International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0003.

[26] H. Rana, "Classification of Malicious Intrusion through ANN-CNN Sequential Classifier," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 27–35, 2024, doi: 10.58325/ijisct.003.02.0088.

[27] Y. Feng, Y. Wang, C. Zeng, and H. Mao, "Artificial intelligence and machine learning in chronic airway diseases: focus on asthma and chronic obstructive pulmonary disease," Int J Med Sci, vol. 18, no. 13, p. 2871, 2021.

[28] N. C. Caballé, J. L. Castillo-Sequera, J. A. Gómez-Pulido, J. M. Gómez-Pulido, and M. L. Polo-Luque, "Machine learning applied to diagnosis of human diseases: A systematic review," Aug. 01, 2020, MDPI AG. doi: 10.3390/app10155135.

[29] M. A. K. Haseeb Ur Rehman Sohaib Masood, "Brain Tumor Classification using Deep Learning Methods," International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0016.

[30] A. Kanwal, K. T. Ahmad, N. Aslam, and others, "Detection of Heart Disease Using Supervised Machine Learning," VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 58–70, 2022.

[31] M. A. M. I. Hamid Ghous Mubasher Malik, "Early Detection of Breast Cancer Tumors Using Linear Discriminant Analysis Feature Selection with Different Classification Methods," International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0008.

[32] A. K. N. M. Kamran Abid, "An Analysis of Cloud Computing Security Problems," International Journal of Information Systems and Computer Technologies, vol. 1, no. 2, 2022, doi: 10.58325/ijisct.001.02.0014.