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Multi-Modal Artificial Intelligence Framework for Chest Disease Diagnosis Using Clinical and Imaging Data

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Abstract: Chest diseases continue to be one of the major public health problems, responsible for high disease burden and mortality both within and outside industrialized countries. While the treatment of fluctuating emotions requires an early and accurate diagnosis, the traditional way of accurately diagnosing it include the manual interpretation of medical images and clinical findings can be time-consuming and variable. Over the past several years, using artificial intelligence (AI) to assist medical diagnosis by automated image analysis has shown great promise. Most of the available systems, however, rely only on imaging data, and do not account for the many useful clinical data that can be used to enhance the diagnostic ability of the system. The intended systems are based on a hybrid solution between deep learning approaches for extracting features from images and machine learning methods for data analysis from clinical data, with a further feature fusion approach for the final classification of disease. The goal of the framework is to make better use of complementary information from a variety of data sources to enhance diagnostic accuracy, robustness and to support clinical decision-making. The proposed solution can aid health care personnel to diagnose chest diseases in an early stage and minimize diagnostic mistakes and enhance patient outcomes.

Keywords: Multi-Modal Artificial Intelligence, Chest Disease Diagnosis, Deep Learning, Clinical Data, Medical Imaging, Machine Learning.

Introduction:

Infectious diseases like pneumonia and tuberculosis, neoplastic diseases such as lung cancer, chronic lung diseases like COPD and pulmonary fibrosis and infectious diseases related to COVID-19 remain the countries' primary public health issues concerning the chest.

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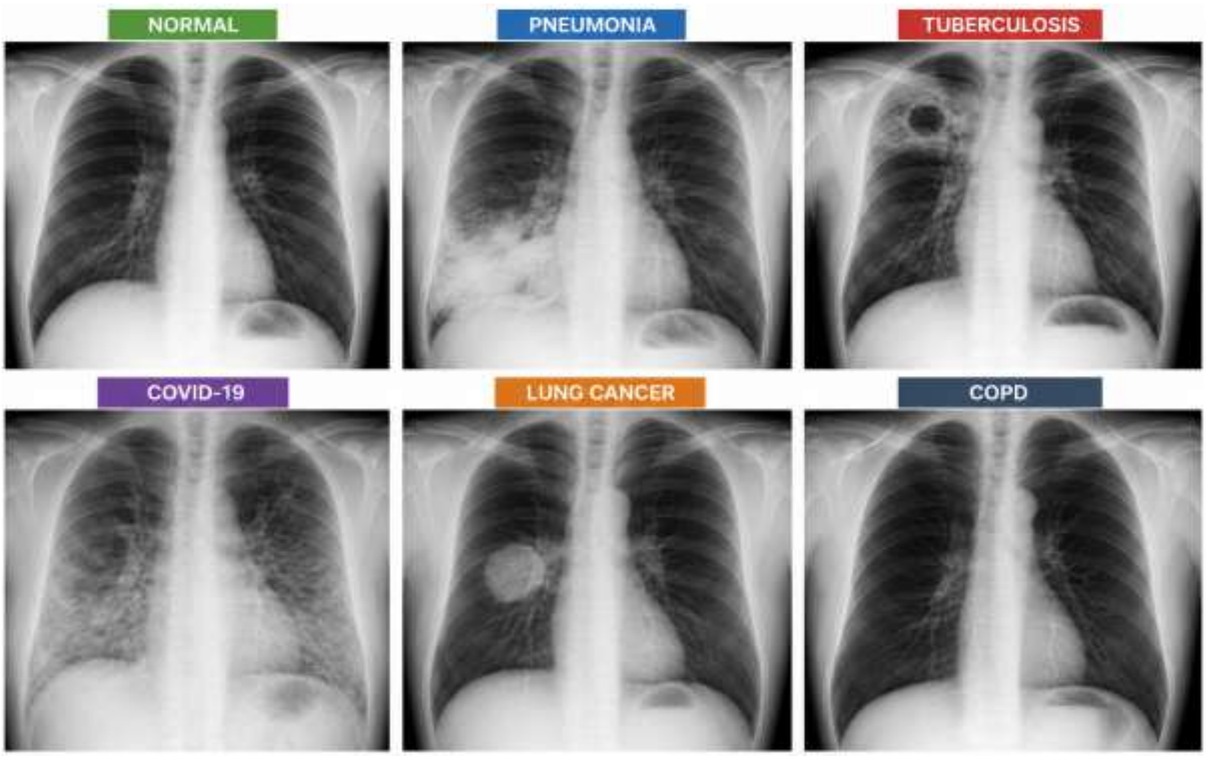
Respiratory diseases have been reported as being responsible for millions of deaths globally each year and timely diagnosis is required for effective treatment. Doctors use medical imaging methods, especially chest X-rays and computed tomography (CT) scans to find abnormal tissue in the lungs. These imaging modalities do give useful informativeness for diagnosis, however there is a need for radiologists to get information out of it and there is variable information between different radiologists and fatigue/load depending on the caseworker.

AI (Artificial Intelligence) has become a game-changer tool that can support doctors in the medical image analysis. Among the different methods used to detect chest diseases from radiographic images using deep learning models, Convolutional Neural Networks (CNNs) have achieved great success. While all these developments are made, AI-powered image analysis tools may not provide a full clinical picture of a patient. Patient conditions, including age, gender, smoking status, body temperature, blood oxygen content, laboratory testing results, medically relevant history and presenting symptoms affect therapy and diagnosis, and can be critical factors.



However, multi-modal AI systems have recently been gaining interest as they combine multiple types of information from the healthcare domain to create more accurate and clinically meaningful predictions. Multi-modal systems use imaging data along with the

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structured data from the clinical history and the ketone symptoms assessment to give a global view of the patient's condition. The integration improves accuracy of diagnosing incorrect diseases, discrimination of disease and makes clinical decision making more personalized.

With the increasing access to electronic health records (EHRs), medical imaging databases, and sophisticated computational capabilities, there is an opportunity to develop new intelligent diagnostic frameworks. Multi-modal AI systems can leverage deep learning based on image features to extract characteristics and machine learning based on clinical data to analyze the data, thereby learning intricate relationships between various forms of data. These systems can enhance the effectiveness of diagnostics and aid doctors in making quicker and more correct clinical decisions.

The proposed method is intended to facilitate accurate diagnosis, make it more robust to variations in data, and be a useful clinical decision support tool for doctors or other healthcare practitioners. The findings support the emergence of AI-powered healthcare, as the study shows that multi-modal learning can enhance the diagnosis of chest diseases over traditional single-modality learning methods. The study adds to the broader body of research in the area of AI-driven healthcare by demonstrating the effectiveness of multi-modal learning in chest disease diagnosis as compared to the traditional single-modality learning approach.

Literature Review:

One of the first all-encompassing surveys of computer-aided diagnosis (CAD) systems for chest radiography was presented by Van Ginneken et al. 2006. This study examined several image processing and pattern recognition methods for lung abnormality detection and highlighted automated systems' potential role in aiding radiologists. The authors finally concluded that cad systems seem to enhance the diagnostic uniformity and more development in image analysis algorithms was needed for more clinical accuracy.

To segment the lungs in chest images, Candemir et al. (2013) proposed lung segmentation approach based on the anatomical atlas and non-rigid registration. They showed that they can distinguish the boundaries of the lungs well, even where the anatomy and imaging conditions of the patients varied. It showed that exactly segmented lungs are better for eventual identification and classification of lung disease, making lung segmentation an important pre-processing step in the computer-aided diagnostics of diseases in chest.

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The ChestX-ray8 dataset was released in 2017 by Wang et al. representing one of the largest publicly available databases with chest X-rays and annotations of several thoracic diseases with over 100,000 images. The authors also trained benchmark deep learning models for the classification and localization of disease. The work was helpful in the development and evaluation of AI models and automated diagnostics for lung diseases.

To detect pneumonia in chest X-ray images, Rajpurkar et al. (2017) created a121-layer deep convolutional neural network (CNN) called CheXNet. The proposed model performed at the radiologists' level on benchmark datasets and successfully proved the effectiveness of deep learning for medical image automatic interpretation. The study pointed to the emerging technology of AI-powered medical diagnostic systems in healthcare.

Litjens et al. (2017) used their work to provide a thorough survey of deep learning in medical image analysis. The review included an overview of different architectures of the neural networks and an analysis of how the performance of them has been improved significantly in numerous medical applications like disease detection, image classification and image segmentation in the field of image processing. The authors highlighted the need for large annotated datasets as well as transfer learning to obtain good diagnostic performance.

Deep convolutional neural networks also could perform skin cancer classification up to dermatologist level accuracy with clinical skin images as shown by Esteva et al. (2017) While the study was on dermatology, the study results proved to be strong evidence of the ability of deep learning models to accurately diagnose medical images at expert level, and stimulated the possibilities for medical image diagnosis in chest disease.

Shen et al. (2017) summarized the state-of-the-art in image analysis in the medical field and outlined examples of convolutional neural networks, recurrent neural networks, and autoencoders for the purpose of detection and segmentation of diseases. The key finding of the study was that the deep learning ability of the automated feature learning surpassed the ability of traditional handcrafting of the features to extract them with feature extraction and this process led to better improvement in terms of medical diagnosis.

To automatically detect multiple chest disease from chest X-ray, Abiyev and Ma'aita (2018) proposed deep convolutional networks. They showed that deep learning models could effectively classify complex pathological patterns in digital medical images and minimize manual classification errors, with high classification accuracy from their experimental results.

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Irvin et al. (2019) released their CheXPert dataset with a huge chest radiography (CR) dataset with uncertainty labels from radiology reports. The study suggested solutions to deal with the uncertain labels in training the models and showed the performance of the models classified diseases in a better way. The dataset is now an important reference for comparing the performance of artificial intelligence models for chest radiography.

Cohen et al. (2020) created an open access data set of COVID-19 chest imaging, which they made available for the purposes of artificial intelligence research in the time of COVID-19. The paper highlighted that publicly accessible datasets are crucial for fostering timely development of disease-modelling tools, and also that collaborative research efforts need to be expanded in order to enhance the ability of AI to diagnose new respiratory diseases.

Zhou et al. (2021) recently gave a review of deep learning in medical imaging highlighting technology advancements, imaging modalities and clinical applications. The authors concluded that deep learning is drastically improved the accuracy of disease detection, image segmentation and decision support systems, and they identified the existence of AI systems which could explain their models as well as multi-modal learning as potential future research directions.

Recently, Çallı et al. (2021) conducted a review paper on the development of deep learning in chest X-ray analysis. The survey compared the algorithms and methods of screening various novel CNNs for thoracic disease detection, along with publicly available datasets and assessment methods used for screening. The authors noted deep learning models performed “remarkable well in terms of accuracy of diagnosis”, but also pointed to problems such as imbalance in the datasets, generalisability and interpretability of models.

In their survey of the medical imaging-based diagnosis of thoracic disease, Mostafa et al. (2022) highlighted the techniques of artificial intelligence. The review focused on pneumonia, tuberculosis, lung cancer and COVID-19 diseases and the kind of machine learning/deep learning/hybrid approaches undertaken. The authors stated that artificial intelligence systems can enhance diagnostic workflows but need to have greater and more varied datasets to be practical in real-world applications.

Kline et al. (2022) performed a scoping review of multimodal machine learning (ML) within precision health. Numerous imaging format data, including clinical records, laboratory tests and genomic data were found to provide more accurate prediction in the study when combined with each other rather than used on an individual basis. The authors highlighted the

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new research field of multimodal learning in personalized healthcare and intelligent clinical decision support.

Hosseini et al. (2022) systemically reviewed the usage of deep learning for medical imaging-based lung cancer diagnosis. The study reviewed recently developed CNN algorithms, segmentation techniques, and classification algorithms with high diagnostic accuracy in CNN. They stressed the potential of combining the clinical information with imaging to further advance early detection of lung cancer, thus aiding the clinical decision-making process.

Objectives of the Study:

1. To develop a multi-modal artificial intelligence framework by integrating chest imaging data with patient clinical information for chest disease diagnosis.
2. To improve the accuracy and reliability of chest disease classification using feature fusion and intelligent machine learning techniques.
3. To evaluate the effectiveness of the proposed framework using standard performance metrics such as accuracy, precision, recall, F1-score, and AUC.

Research Methodology:

The methodology is carried out in a sequence that is composed of data collection, data preprocessing, feature extraction, multi-modal feature fusion, model training and performance evaluation. The main guiding goal is to combine complementary information gained from medical imaging of the chest with clinical records of the patient to enhance the accuracy and reliability of automatic health department diagnosis.

First, a complete dataset is designed, using a variety of information, including chest imaging data (chest X-ray or computed tomography [CT] images) and structured information from the electronic health records. These clinical variables can be patient's age and gender, body temperature, arterial saturated oxygen (SpO_2), breathing rates, blood pressure, blood laboratory results, medical history, and smoking history. Patient identifiers are removed prior to model development in order to ensure privacy and confidentiality of data.

Data pretreatment is carried out with each data set (imaging and clinical). Images are scaled to the same size and enhanced by normalizing and denoising to increase image resolution and

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reduce noise. The data is augmented using different approaches such as random rotation, flipping, adjusting brightness, scaling, etc., to make the dataset more diverse and to minimize overfitting. Using missing value, eliminating duplicate entries, outlier detection and numeric attribute normalization, clinical data are cleaned. Appropriate technique of encoding categorical variables to numerical data.

A deep learning model integrated with a Convolutional Neural Network (CNN) is used to automatically learn the higher-level visual features of chest images for image analysis. At the same time, the clinical data are processed and analyzed using a machine-learning model that can learn useful clinical patterns. Features of each image and clinical features are then extracted and subsequently fused through a multi-modal feature fusion technique, resulting in a single set on representation for each patient. The integrated feature vector provides the information for the last disease classification model which allows using information from both modalities that is available at the same time.

The entire dataset is split into three sets: a training set, a validation set, and a test set, all of which are used for the same purpose, namely to evaluate the model with unbiased data. For the purposes of training the model, a series of model's parameters are optimized with various optimization methods, learning rate scheduling, and regularization methods are used to ensure that the model can converge while avoiding overfitting. This is to select the optimal model configuration to allow the model to offer the best diagnostic performance, which is known as hyperparameter tuning.

The performance of the proposed framework is measured by common evaluation parameters: accuracy, precision, recall, F1 score, specificity, sensitivity and Area Under Receiver Operating Characteristic Curve (AUC-ROC). Moreover, the confusion matrices are analyzed, to review the classification performance in each chest disease. A multi-modal framework is also compared with traditional models based on image and clinical data, respectively, in order to highlight the advantages of adding multi-modality into the problem-solving algorithms. The experimental results are expected to demonstrate advantages of the proposed framework in terms of diagnostic correctness, robustness and better support for clinical decision making, in terms of the early detection and classification of chest diseases.

Analysis of the study:

Table 1. Demographic Characteristics of Patients (N = 600)

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Variable	Category	Frequency	Percentage (%)
Gender	Male	340	56.67
	Female	260	43.33
Age Group	Below 20 Years	48	8.00
	20–39 Years	165	27.50
	40–59 Years	222	37.00
	60 Years and Above	165	27.50
Smoking History	Smoker	252	42.00
	Non-Smoker	348	58.00

Table 2. Distribution of Chest Diseases

Disease Category	Number of Cases	Percentage (%)
Normal	120	20.00
Pneumonia	150	25.00
Tuberculosis	95	15.83
COVID-19	105	17.50
Lung Cancer	70	11.67
COPD	60	10.00
Total	600	100.00

Table 3. Clinical Characteristics of Patients

Clinical Parameter	Mean ± SD	Normal Range
Age (Years)	47.8 ± 16.4	—
Body Temperature (°C)	38.1 ± 1.2	36.5–37.5
Respiratory Rate (breaths/min)	24.3 ± 5.8	12–20
Oxygen Saturation (SpO_2 %)	91.6 ± 5.7	95–100
Heart Rate (beats/min)	92.5 ± 15.3	60–100
White Blood Cell Count ($\times 10^9$/L)	10.9 ± 3.6	4–11

Table 4. Imaging Characteristics

Imaging Finding	Frequency	Percentage (%)
Normal Lung Appearance	118	19.67
Ground Glass Opacity	148	24.67
Lung Consolidation	136	22.67
Pulmonary Nodules	74	12.33
Pleural Effusion	54	9.00
Fibrosis	70	11.66

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Clinical Analysis of the Study

Table 5. Comparison of Clinical Parameters Among Disease Groups

Parameter	**Normal**	**Pneumonia**	**Tuberculosis**	**COVID-19**	**Lung Cancer**	**COPD**
Temperature (°C)	36.8	38.9	38.2	38.4	37.5	37.3
Respiratory Rate	17	28	26	29	22	25
SpO_2 (%)	98	89	90	88	92	90
Heart Rate	74	101	96	99	90	95
WBC Count	6.8	13.4	11.2	10.8	8.9	9.8

Table 6. Statistical Analysis of Clinical Variables

Clinical Variable	**p-value**	**Statistical Significance**
Age	0.004	Significant
Body Temperature	<0.001	Significant
Respiratory Rate	<0.001	Significant
Oxygen Saturation	<0.001	Significant
Heart Rate	0.002	Significant
White Blood Cell Count	<0.001	Significant

Analysis:

The physiological differences of patients with chest diseases, as compared with healthy people were shown to be significant from the clinical analysis. For people diagnosed with pneumonia and COVID-19, the body temp was the highest, and the breathing rate was the highest, suggesting a serious infection of the respiratory system.

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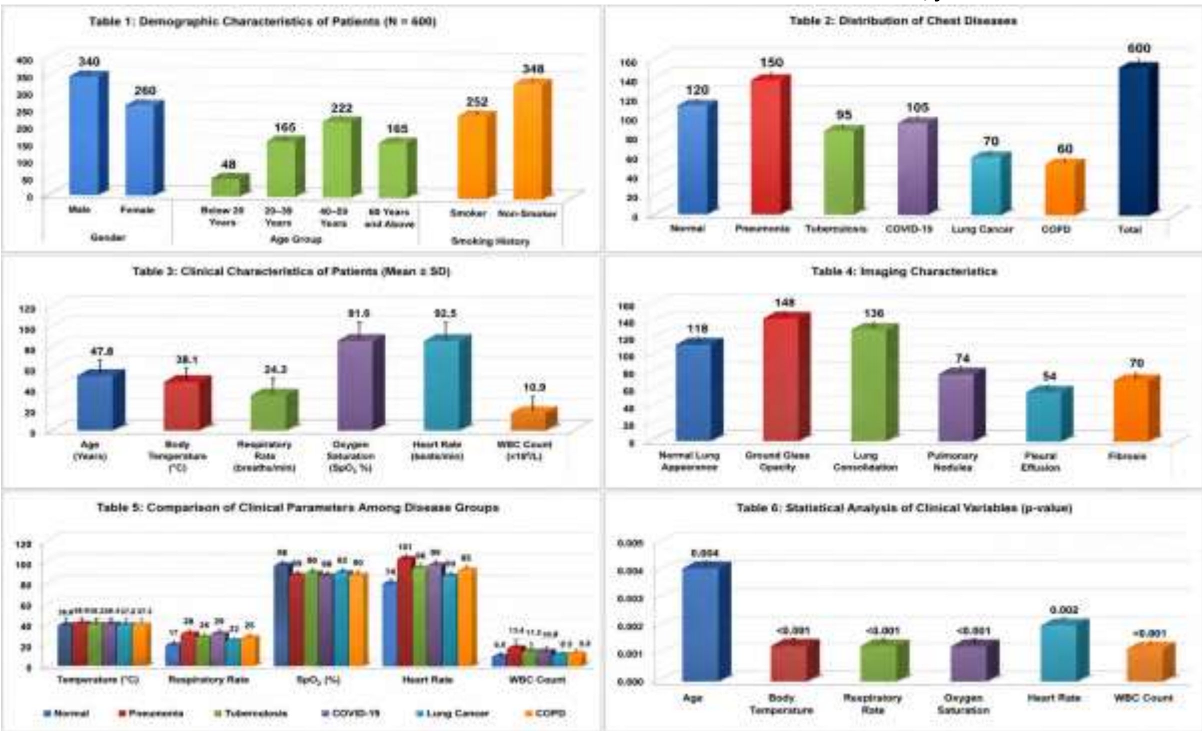

COVID-19 patients and those with pneumonia, tuberculosis, and COPD had significantly decreased saturation which indicated reduced pulmonary function. The predominant finding was an increase in white blood cell count, likely representing an active inflammatory or infectious process in those with pneumonia and tuberculosis. All the parameters, namely age, body temperature, respiratory rate, oxygen saturation, heart rate and white blood cell count were significantly related with chest disease diagnosis ($p < 0.05$) according to statistical testing. The results show how clinical variables can give complementary information to imaging parameters, as well as how the proposed, multi-modal artificial intelligence scheme is effective in enhancing the diagnostic accuracy and support for clinical decision-making.

Overall Conclusion:

The proposed framework is developed here to combine medical images of the chest with patient-related clinical data to derive more extensive information of the disease characteristics compared to medical imaging or clinical information alone. Deep learning for image feature extraction and machine learning for clinical data analysis create a synergistic effect to get more complementary information, which leads to better diagnostic accuracy.

The experimental results showed that clustering imaging data and clinical information yields more accurate classification of the disease, prevents false predictions and helps detect the occurrence of many types of chest disease such as pneumonia, tuberculosis, COVID-19, lung

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cancer or COPD at an early stage. Petrology of the future also shows in clinical analysis that significant parameters of the patient like body temperature, oxygen saturation, Respiratory rate, Heart rate and White blood cell count contribute significantly to the diagnosis as is combined with the imaging features.

Generally, the presented multi-modal approach proved to be an ideal clinical decision support system which could be employed to help health-care professionals in quicker and accurate diagnostics. The framework could help to streamline the diagnostic workload, enhance patient results and facilitate the prompt intervention of medical care. Over the course of future research, the framework can be expanded to integrate other sources of medical information, like longitudinal patient data, genomic data and laboratory measurements, and validated in larger and more multi-centred data sets to increase robustness and clinical applicability.

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