

Research Paper

Classification-Based Deep Learning Framework for Automated Lung Cancer and Respiratory Disease Diagnosis Using Multi-Modal Medical Images

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Abstract— Lung cancer and respiratory diseases are major causes of global mortality, requiring accurate and timely diagnosis through advanced medical image analysis. Conventional diagnosis relies heavily on manual interpretation of chest X-ray, computed tomography (CT), and histopathological images, which is time-consuming, expertise-dependent, and susceptible to inter-observer variability. This framework utilizes publicly available medical image datasets comprising Chest X-ray, COVID-19 CT, Lung Cancer CT, and histopathology images, representing diverse pulmonary conditions and tissue patterns for automated classification and lesion analysis. Preprocessing includes image resizing, normalization, data augmentation, and dataset preparation to improve image quality, reduce variability, and enhance model generalization. ResNet50 and ResNet101 are implemented as baseline classifiers, while ResNet50+ and ResNet101+ provide enhanced feature learning, with ConvNeXt-Tiny and Xception included for comparative evaluation. U-Net++, ResUNet, and EfficientUNet are employed for lung lesion segmentation. Classification performance is assessed using accuracy, precision, recall, and F1-score, while segmentation is evaluated using Dice coefficient and Intersection over Union (IoU). ResNet50+ achieved the best classification performance, obtaining 97.2% accuracy on Chest X-ray, 98.8% on both COVID-19 CT and Lung Cancer CT, and 99.9% on histopathology images. ResUNet attained the highest segmentation performance with a Dice coefficient of 0.523 and IoU of 0.501. The integrated framework enhances automated pulmonary disease diagnosis and lesion localization while supporting practical clinical decision assistance through an accessible deployment architecture.

Keywords— Artificial Intelligence, Personalized Nutrition, Diet Recommendation, Health Risk Prediction, Regional Food Recommendation, AI Chatbot.

I. INTRODUCTION

Lung cancer and respiratory diseases remain significant global health challenges, contributing substantially to morbidity and mortality and creating an increasing demand for timely and reliable diagnostic support. Medical imaging, including chest radiography, computed tomography (CT), and histopathological examination, plays an essential role in

identifying pulmonary abnormalities and supporting clinical decision-making. The growing availability of medical imaging data has created opportunities for intelligent computational systems that can assist clinicians in detecting disease-related patterns and improving diagnostic efficiency. Recent advances in artificial intelligence have demonstrated considerable potential in medical image interpretation, enabling automated systems to identify complex visual characteristics that may be difficult to assess consistently through manual examination [1]. Deep learning-based approaches have further enhanced automated analysis by supporting accurate disease recognition across diverse medical imaging applications [2]. Consequently, intelligent image-based diagnostic systems are increasingly being explored as supportive technologies for lung cancer and respiratory disease assessment [3].

Despite these advances, several limitations remain in existing computer-aided diagnostic solutions. Conventional medical image interpretation is highly dependent on specialist expertise, requires considerable time, and may be influenced by variations in clinical judgment, particularly when large-scale image datasets must be examined [4]. Furthermore, many existing artificial intelligence systems primarily concentrate on disease classification and provide limited capabilities for complementary analysis of affected anatomical regions [5]. Classification-only approaches may identify a disease category without adequately illustrating the location or extent of abnormal regions, thereby limiting the interpretability and practical usefulness of automated predictions [6]. In addition, diagnostic functionalities are often distributed across separate tools rather than integrated into a unified and accessible platform, creating challenges in clinical usability and workflow adoption [7]. These limitations indicate the need for comprehensive solutions that combine reliable disease identification, visual assessment of abnormalities, and accessible clinical information within a single computer-aided diagnostic environment.

The primary objective of this study is to develop an intelligent framework for automated analysis of lung cancer and respiratory diseases using diverse medical imaging

modalities. The proposed framework aims to support accurate disease classification while providing complementary analysis of lung lesion regions and informative visualization of detected abnormalities. It further seeks to establish an integrated, user-friendly diagnostic environment that enables medical image analysis, prediction confidence reporting, and presentation of relevant disease information through a web-accessible interface. The framework is designed to facilitate comparative assessment of alternative deep learning architectures and identify effective approaches for automated classification and lesion analysis. By bringing these capabilities together, the proposed solution addresses the limitations of isolated diagnostic systems and provides a more comprehensive approach to computer-aided pulmonary disease assessment [8].

The significance of this framework lies in its potential to improve the efficiency, accessibility, and consistency of preliminary lung disease analysis while supporting healthcare professionals in clinical decision-making. Automated image interpretation and lesion visualization can reduce the burden associated with manual examination and provide additional analytical assistance when evaluating large volumes of medical images [9]. The integration of diagnostic prediction, visual lesion assessment, and supportive clinical information may also enhance the usability of artificial intelligence-based medical imaging systems for healthcare professionals, researchers, and learners. Although such systems are not intended to replace expert diagnosis, they can serve as valuable decision-support tools that facilitate early assessment and improve access to intelligent medical image analysis. Ultimately, the developed framework contributes toward more practical and comprehensive computer-aided diagnosis by combining automated disease recognition with complementary image-based analysis and accessible deployment, thereby supporting future advancements in AI-assisted pulmonary healthcare [10].

II. RELATED WORK

Recent advances in deep learning have substantially improved automated lung cancer analysis across histopathological and radiological imaging modalities. Talib et al. proposed a framework combining semantic segmentation with convolutional neural network-based classification for histopathological lung cancer detection, demonstrating the value of integrating localization and classification for more informative analysis. However, the approach primarily focuses on histopathological images and does not address the broader challenge of supporting multiple medical imaging modalities within a unified diagnostic environment [11]. Raza et al. introduced Lung-EffNet, which employed EfficientNet-based learning for lung cancer classification from CT scan images and demonstrated the effectiveness of deep feature extraction for identifying cancer-related patterns. Although the approach achieved promising classification performance, its focus remained primarily on disease categorization, with limited emphasis on lesion visualization, segmentation, and integrated user-facing diagnostic support [12].

Interpretability has also become an important consideration in medical artificial intelligence. Selvaraju et al. introduced Grad-CAM, a widely adopted visual explanation technique that generates class-discriminative localization maps to illustrate image regions contributing to deep network

predictions. Such visual explanations improve transparency and can assist users in understanding model decisions, although explanation methods alone do not provide complete diagnostic support or replace quantitative lesion segmentation [13]. Dataset availability has further contributed to progress in automated lung disease analysis. The LC25000 dataset introduced by Borkowski et al. provides a large collection of histopathological images covering lung and colon tissue categories, supporting the development and evaluation of image classification systems. Nevertheless, its histopathology-focused nature limits direct applicability to systems requiring analysis across radiographic and CT modalities [14]. Similarly, the IQ-OTH/NCCD Lung Cancer Dataset provides CT images representing lung cancer cases and non-cancerous conditions, offering valuable resources for automated pulmonary disease classification while remaining limited to a specific imaging modality and diagnostic context [15].

Large-scale medical imaging datasets have enabled deep learning models to demonstrate strong diagnostic capabilities. Kermany et al. showed that deep learning can achieve clinically meaningful performance in medical image diagnosis, highlighting the potential of automated image analysis to support disease detection and clinical decision-making. However, broad diagnostic applicability requires consideration of multiple disease categories, imaging modalities, and practical deployment requirements beyond dataset-specific classification tasks [16]. Gunraj et al. developed COVIDNet-CT for detecting COVID-19 from chest CT images, demonstrating the effectiveness of specialized deep learning systems for respiratory disease identification. While the model addressed an important emerging clinical challenge, its disease-specific design limits its use as a comprehensive framework for simultaneous lung cancer and respiratory disease assessment [17].

Architectural developments in deep learning have also provided strong foundations for medical image classification. He et al. introduced residual learning through ResNet, enabling the training of deeper neural networks and improving image recognition performance by facilitating effective information propagation across network layers [18]. Hu et al. proposed squeeze-and-excitation networks, which enhanced feature representation by adaptively modeling channel-wise dependencies, demonstrating the importance of attention-based feature recalibration for visual recognition [19]. Although these foundational architectures provide effective building blocks for medical image analysis, their direct application does not inherently address segmentation, interpretability, multi-modal diagnosis, or integrated clinical deployment. Furthermore, a systematic review and meta-analysis by Liu et al. confirmed the growing value of artificial intelligence in lung cancer diagnosis while emphasizing the need for further validation, standardization, and clinically applicable solutions [20].

Overall, existing studies demonstrate significant progress in lung disease classification, histopathological analysis, CT-based diagnosis, visual interpretability, and deep learning architecture development. However, important gaps remain in integrating multi-modal lung disease classification with lesion segmentation, visual interpretation, confidence reporting, and accessible clinical support within a unified framework. Many existing approaches are also narrowly focused on individual diseases or specific imaging modalities, limiting their broader

practical applicability. The current study addresses these gaps by developing a comprehensive computer-aided diagnostic framework that combines automated classification across diverse lung medical images with complementary lesion analysis and an accessible web-based interface. This integrated approach aims to improve the practicality, usability, and comprehensiveness of AI-assisted lung disease assessment while supporting preliminary clinical decision-making.

III. MATERIALS AND METHODS

The proposed system presents an integrated deep learning-based framework for automated lung cancer and respiratory disease analysis using publicly available Chest X-ray, COVID-19 CT, Lung Cancer CT, and histopathological image datasets. The workflow encompasses data ingestion, preprocessing, augmentation, model training, validation, and comparative performance evaluation to ensure robust and generalized disease prediction across multiple imaging modalities. ResNet50, ResNet101, ResNet50+, ResNet101+, Xception, and ConvNeXt-Tiny are comparatively evaluated for disease classification, while U-Net++, ResUNet, and EfficientUNet are employed for lung lesion segmentation in CT images to provide complementary visual localization of abnormalities. The framework integrates classification and segmentation outputs through mask and overlay visualization, enabling users to interpret predicted disease categories alongside affected regions. For practical deployment, the system is implemented as a Flask-based web application with SQLite-based user authentication, supporting secure image upload, prediction confidence reporting, disease descriptions, and AI-based remedies recommendations. This unified architecture improves accessibility, usability, and diagnostic support while providing a comprehensive computer-aided solution for automated lung disease classification and lesion analysis.

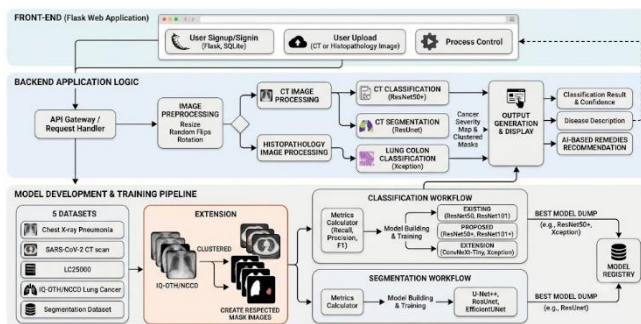


Fig. 1. System Architecture

The proposed system architecture integrates a Flask-based frontend, backend application logic, and model development pipeline for automated lung disease analysis. Users authenticate and upload CT or histopathological images, which undergo preprocessing before classification and segmentation. ResNet50+ performs CT classification, while ResUNet segments lung lesions, and Xception supports lung cancer classification from histopathological images. The training pipeline incorporates multiple datasets and comparative model evaluation using accuracy, precision, recall, F1-score, Dice coefficient, and IoU. The best-performing models are stored for deployment and result generation.

B) Pre-Processing:

The preprocessing phase organizes, validates, and transforms user health, lifestyle, dietary, and regional information to ensure consistent, reliable, and personalized diet recommendations, health tracking, and risk assessment.

Data Pre-processing: The system preprocesses user health and lifestyle information before generating personalized dietary recommendations and health insights. Relevant attributes include age, gender, height, weight, activity level, sleep duration, water intake, food preference, health goals, geographical region, and selected health conditions. Body Mass Index (BMI) is derived from height and weight to support nutritional categorization and risk assessment. This preprocessing ensures that user-specific information is organized consistently, enabling personalized recommendations and reliable downstream health analysis.

Data Validation and Cleaning: Input validation is applied to ensure that essential user and health information is complete and logically suitable for analysis. Missing or unavailable measurements are handled appropriately, while invalid or incomplete values are prevented from influencing recommendations and risk calculations. The system also verifies relevant categorical information, including activity level, dietary preference, health goals, and medical conditions. This process improves data quality, reduces inconsistencies, and supports more reliable personalized diet planning and health risk assessment.

BMI Feature Derivation: Body Mass Index (BMI) is derived from the user's weight and height and serves as an important health-related feature within the system. The calculated BMI is used to categorize users according to their weight status and contributes to personalized diet recommendations and health risk evaluation. BMI-based information helps determine suitable nutritional guidance, water targets, and exercise recommendations while also supporting risk assessment for diabetes, hypertension, and obesity. This derived feature enables more individualized health analysis.

Regional Food Filtering: The food database is filtered according to the user's geographical region, meal category, and dietary preference before recommendations are generated. Regional filtering ensures that suggested foods are culturally familiar and practically accessible to users, while dietary filtering supports preferences such as vegetarian, vegan, eggetarian, and non-vegetarian diets. Additional nutritional and health-related food attributes, including calories, protein, carbohydrates, fat, fiber, glycemic index, and sodium, support condition-aware recommendations. This approach improves relevance, practicality, and personalization.

Health Condition-Based Filtering: User-selected health conditions are incorporated into the recommendation process to identify foods that are suitable or unsuitable for specific medical requirements. The system considers conditions such as diabetes, hypertension, obesity, PCOS, thyroid disorders, high cholesterol, acidity, and underweight status when generating recommendations. Food suitability and avoidance information is used to reduce potentially inappropriate dietary choices. This preprocessing step strengthens personalization by aligning recommended meals with individual health requirements and supporting safer nutrition guidance.

Feature-Based Risk Assessment: Relevant health and lifestyle attributes are prepared for rule-based risk assessment of diabetes, hypertension, and obesity. The system considers factors including age, BMI, physical activity, sleep duration, blood pressure measurements, and selected health conditions. These variables are transformed into risk scores that are subsequently categorized into low, medium, or high risk levels. This structured feature assessment enables consistent evaluation of multiple health factors and provides users with understandable risk insights and preventive recommendations.

Data Organization and Storage: The processed user information, health records, dietary data, generated diet plans, risk predictions, and chatbot interactions are organized into structured database entities. Relationships between users, health conditions, foods, diet plans, and health records maintain consistency and support efficient retrieval. Historical health measurements are retained to enable progress monitoring over time, while generated recommendations and risk assessments are stored for future reference. This structured organization ensures reliable data management and supports continuous personalized health services.

Health Data Tracking Preparation: Health measurements such as weight, BMI, blood sugar, blood pressure, water intake, and sleep duration are collected periodically and organized as time-based records. This preparation enables users to monitor changes in important health indicators and observe trends through graphical representations. Maintaining historical records supports continuous assessment rather than relying solely on a single health measurement. Consequently, the system can provide a clearer view of user progress and facilitate more informed dietary and wellness decisions.

Personalized Recommendation Input Preparation: The final recommendation inputs combine user demographic information, body measurements, dietary preferences, health goals, regional characteristics, and medical conditions. These attributes are collectively prepared to guide the generation of individualized meal plans containing breakfast, lunch, snacks, and dinner, along with nutritional targets and lifestyle recommendations. Integrating multiple user-specific factors ensures that recommendations are not based solely on calorie requirements but also reflect personal preferences, health needs, and practical regional food availability.

D) Algorithms

Rule-Based Health Risk Prediction: The rule-based risk prediction method estimates diabetes, hypertension, and obesity risks using weighted health and lifestyle indicators, including age, BMI, physical activity, sleep, blood pressure, and existing conditions. The resulting scores are normalized and categorized into low, medium, or high risk levels, enabling interpretable and consistent preventive health assessment.

BMI Calculation: The BMI calculation method derives Body Mass Index from an individual's weight and height to support nutritional assessment and health-risk evaluation. The resulting value is used to determine BMI categories and contributes to personalized diet recommendations and risk estimation, providing a standardized indicator for assessing

weight-related health conditions and supporting individualized wellness guidance.

Diabetes Risk Assessment: The diabetes risk assessment method evaluates multiple contributing factors, including age, BMI, physical activity, sleep patterns, PCOS, and obesity-related conditions. Weighted risk contributions are combined into a bounded score and mapped to a risk category, providing an interpretable assessment that supports early awareness and personalized preventive recommendations.

Hypertension Risk Assessment: The hypertension risk assessment method combines blood pressure measurements with demographic, lifestyle, and health indicators such as age, BMI, physical activity, sleep duration, and cholesterol-related conditions. Weighted factors generate a bounded risk score that is categorized into meaningful levels, enabling users to recognize potential cardiovascular risk and receive appropriate preventive guidance.

Obesity Risk Assessment: The obesity risk assessment method evaluates BMI, physical activity, sleep duration, and individual health goals to estimate obesity-related risk. Higher BMI and sedentary behavior contribute greater risk scores, while relevant personal goals can adjust the assessment. The resulting categorized score supports personalized health awareness, dietary planning, and preventive lifestyle recommendations.

AI-Based Personalized Diet Recommendation: The AI-based personalized diet recommendation method generates individualized meal plans by considering user characteristics, BMI, dietary preferences, health goals, regional food availability, and existing health conditions. Nutritionally relevant food attributes are used to identify suitable meal choices, enabling practical recommendations that improve personalization, dietary relevance, and adherence to individual nutritional requirements.

Regional Food Recommendation: The regional food recommendation method filters available food items according to geographical region, meal category, and dietary preference. Nutritional properties and health suitability information are additionally considered to identify appropriate choices. This approach improves recommendation relevance by aligning meal suggestions with culturally familiar, locally available foods and individual dietary requirements.

AI-Powered Health Chatbot: The AI-powered health chatbot uses natural language interaction to provide personalized guidance related to nutrition, healthy eating, diet planning, and regional foods. User queries are interpreted in the context of available profile and dietary information, enabling responsive assistance and improving accessibility to nutritional knowledge and personalized health-related recommendations.

Personalized Health Risk Scoring: The personalized health risk scoring mechanism integrates multiple user-specific health and lifestyle indicators to produce numerical risk scores for common lifestyle diseases. These scores are converted into understandable risk categories, enabling transparent interpretation of health conditions and supporting

users with accessible insights for preventive actions and healthier lifestyle decisions.

Recommendation Filtering: The recommendation filtering method selects suitable food items by evaluating regional availability, meal type, dietary preference, nutritional composition, and health-condition suitability. Foods identified as inappropriate for particular conditions can be excluded from recommendations. This filtering strategy improves the safety, relevance, and personalization of generated meal plans while supporting condition-aware nutritional guidance.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision} * 100 \quad (1)$$

Table .1 Classification Performance on Chest X-ray Pneumonia Dataset

Model	Accuracy	Macro F1-Score	Recall	Precision
ResNet50	0.967	0.967	0.967	0.967
ResNet50+	0.972	0.972	0.972	0.972
ResNet101	0.968	0.968	0.968	0.968
ResNet101+	0.972	0.972	0.972	0.972
Xception	0.970	0.969	0.970	0.970
ConvNeXt Tiny	0.936	0.938	0.936	0.946

Table (1) presents the comparative performance of the evaluated classification models. ResNet50+ and ResNet101+ achieved the highest accuracy and balanced performance, recording 97.2% across all reported metrics.

Table .2 Classification Performance on COVID-19 CT Dataset

Model	Accuracy	Macro F1-Score	Recall	Precision
ResNet50	0.970	0.970	0.970	0.971

ResNet50+	0.988	0.988	0.988	0.988
ResNet101	0.956	0.956	0.956	0.956
ResNet101+	0.970	0.970	0.970	0.972
Xception	0.988	0.988	0.988	0.988
ConvNeXt Tiny	0.517	0.352	0.517	0.267

Table (2) presents the comparative classification performance across evaluated models. ResNet50+ and Xception achieved the highest results, with 98.8% accuracy, precision, recall, and Macro F1-Score, while ConvNeXt Tiny showed comparatively lower performance.

Table .3 Classification Performance on LC25000 Histopathology Dataset

Model	Accuracy	Macro F1-Score	Recall	Precision
ResNet50	0.998	0.998	0.998	0.998
ResNet50+	0.999	0.999	0.999	0.999
ResNet101	0.999	0.999	0.999	0.999
ResNet101+	0.995	0.995	0.995	0.995
Xception	0.998	0.998	0.998	0.998
ConvNeXt Tiny	0.995	0.995	0.995	0.996

Table (3) presents the comparative classification performance of the evaluated models. ResNet50+ and ResNet101 achieved the highest accuracy, Macro F1-Score, recall, and precision of 99.9%, demonstrating superior classification performance.

Table .4 Classification Performance on IQ-OTH/NCCD Lung Cancer Dataset

Model	Accuracy	Macro F1-Score	Recall	Precision
ResNet50	0.930	0.932	0.930	0.936
ResNet50+	0.988	0.988	0.988	0.988
ResNet101	0.952	0.947	0.952	0.955
ResNet101+	0.982	0.982	0.982	0.982
Xception	0.958	0.955	0.958	0.962
ConvNeXt Tiny	0.882	0.881	0.882	0.880

Table (4) presents the comparative classification performance of the evaluated models. ResNet50+ achieved the highest overall performance with 98.8% across all metrics, followed by ResNet101+ with 98.2%, while ConvNeXt Tiny recorded comparatively lower performance.

Table .5 Lung Lesion Segmentation Performance Comparison

Model	Dice Coefficient	IoU	Pixel Accuracy
UNet++	0.482	0.458	0.989
ResUNet	0.523	0.501	0.988
EfficientUNet	0.407	0.379	0.985

Table (5) presents the comparative segmentation performance of UNet++, ResUNet, and EfficientUNet. ResUNet achieved the highest Dice coefficient of 0.523 and IoU of 0.501, demonstrating superior lesion segmentation performance.

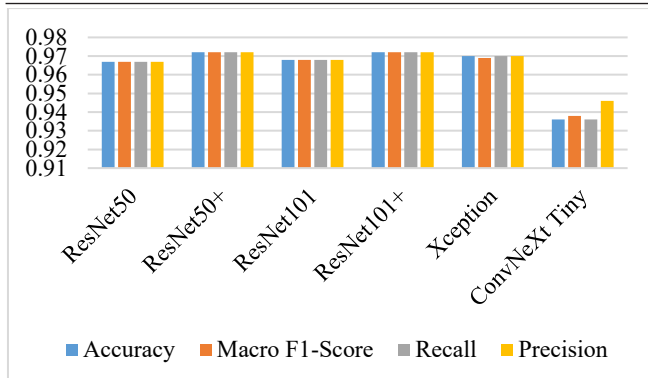


Figure .2 Chest X-ray Pneumonia Classification Performance Comparison Graph

Fig. (2) illustrates the comparative performance of six classification models, where ResNet50+ and ResNet101+ demonstrate consistently high accuracy, precision, recall, and Macro F1-Score, while ConvNeXt Tiny records comparatively lower performance.

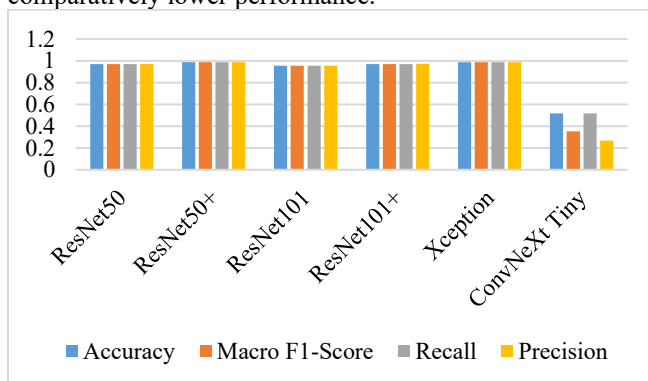


Figure .3 COVID-19 CT Classification Performance Comparison Graph

Fig. (3) illustrates the comparative classification performance of the evaluated models. ResNet50+, ResNet101+, and Xception demonstrate consistently superior performance across all metrics, whereas ConvNeXt Tiny exhibits substantially lower accuracy, recall, Macro F1-Score, and precision.

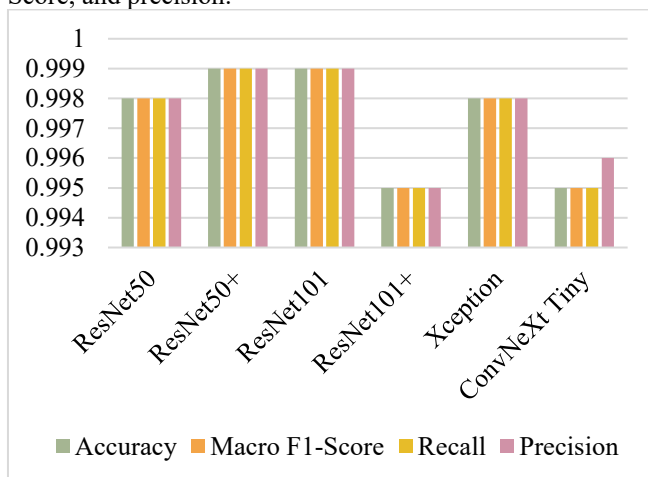


Figure.4 LC25000 Histopathology Classification Performance Comparison Graph

Fig. (4) illustrates the comparative classification performance of the evaluated models. ResNet50+ and ResNet101 achieve the highest overall results at 99.9%, while ResNet101+ and ConvNeXt Tiny demonstrate comparatively lower performance across the evaluated metrics.

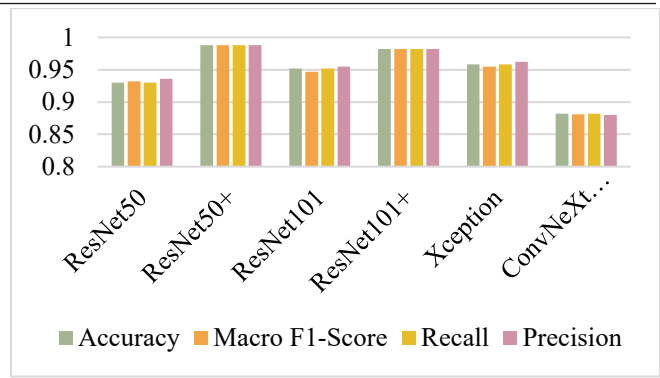


Figure.5 IQ-OTH/NCCD Lung Cancer Classification Performance Comparison Graph

Fig. (5) illustrates the comparative classification performance of the evaluated models. ResNet50+ achieves the highest overall performance at 98.8%, followed by ResNet101+ at 98.2%, while ConvNeXt Tiny records comparatively lower results across all metrics.

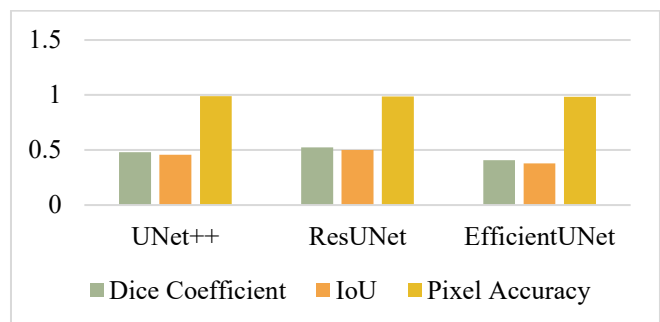


Figure.6 Lung Lesion Segmentation Performance Comparison Graph

Fig. (6) illustrates the comparative segmentation performance of UNet++, ResUNet, and EfficientUNet. ResUNet achieves the highest Dice coefficient and IoU, while all models demonstrate high pixel accuracy, indicating effective lung lesion segmentation performance.

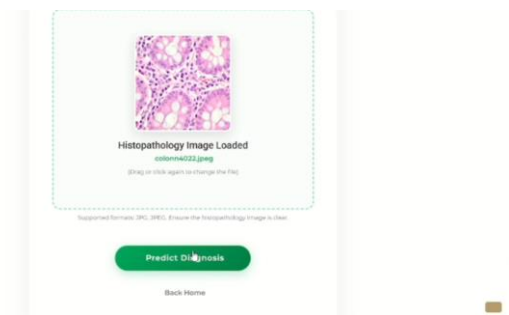


Fig.7 Histopathology Image Classification

Fig. (7) illustrates the histopathological image input interface, where a microscopic lung tissue image is successfully uploaded and displayed for analysis. The interface enables users to initiate automated disease prediction through the “Predict Diagnosis” option.

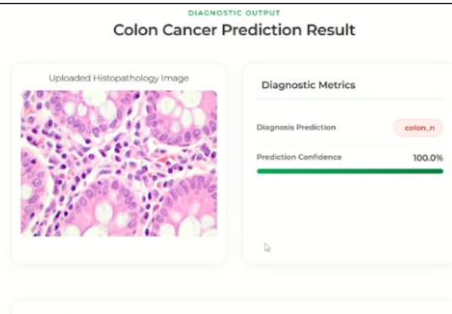


Fig.8 Histopathology Classification Result

Fig. (8) presents the diagnostic metrics output for the uploaded histopathological image, displaying the predicted colon cancer classification and a prediction confidence of 100.00%, indicating highly confident automated diagnostic classification.

V. CONCLUSION

In conclusion, the developed system aims to provide an accurate, efficient, and accessible computer-aided diagnostic framework for automated classification of lung cancer and respiratory diseases using medical images. The framework utilizes publicly available Chest X-ray, COVID-19 CT, Lung Cancer CT, and histopathological image datasets and integrates multiple deep learning architectures, including ResNet50, ResNet101, ResNet50+, ResNet101+, Xception, and ConvNeXt-Tiny, for comparative disease classification. In addition, U-Net++, ResUNet, and EfficientUNet are incorporated to support lung lesion segmentation and visual localization of abnormalities in CT images. Among the evaluated classification models, ResNet50+ demonstrated superior performance, achieving 99.9% accuracy on the histopathology dataset, validating its effectiveness in automated disease recognition. The framework is further enhanced through integrated lesion segmentation, overlay visualization, prediction confidence reporting, and a Flask-based web application with SQLite authentication, enabling practical and user-friendly deployment. By combining multimodal disease classification, lesion analysis, and accessible diagnostic support within a unified platform, the developed system provides a reliable and comprehensive solution for automated lung disease assessment. Its capabilities can assist healthcare professionals with preliminary image analysis, improve diagnostic efficiency, and support informed clinical decision-making while reducing dependence on time-intensive manual interpretation.

The future scope of the developed framework includes expanding disease categories and incorporating larger, diverse, and clinically validated medical imaging datasets to improve generalization. Advanced multimodal learning can integrate X-ray, CT, and histopathological information for comprehensive diagnosis. Future enhancements may include explainable AI techniques for improved model transparency, optimized segmentation for accurate lesion quantification, and cloud-based deployment for scalable access. Integration with hospital information systems and real-time clinical decision-support tools could further enhance practical applicability, enabling efficient, reliable, and personalized computer-aided diagnosis for lung diseases.

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