Frontiers in Life Sciences Research
Vol. 1, No. 4, Oct - Dec 2025, pp. 41-48
ISSN: 3107-5274, DOI: https://doi.org/10.17051/FLSR/01.04.07

Ultrasound Image Synthesis Using Generative Ai For Lung Consolidation Detection

Sajna M[1], Geetha E[2]

[1]PG Scholar, Department of Medical Electronics, Sengunthar Engineering College, Thiruchengode, Tamil Nadu, India-637205, Email: msajnaismail@gmail.com
[2]Professor, Department of Medical Electronics, Sengunthar Engineering College, Thiruchengode, TamilNadu, India– 637205

Article Info

Article history:

Received : 21.10.2025
Revised : 07.11.2025
Accepted : 08.12.2025

Keywords:

lung consolidation,
ultrasound imaging,
generative AI,
GAN, VAE,
synthetic data,
machine learning,
MATLAB.

ABSTRACT

Lung consolidation remains difficult to diagnose accurately due to the limited availability of large, well-annotated ultrasound datasets, which limits the performance of machine learning models built for clinical support. In order to tackle this challenge, this proposal presents a generative AI-driven framework able to synthesize realistic lung ultrasound images representative of different pathological patterns related to consolidation, aiming at improving the training pipelines by supplying high-fidelity synthetic data that enhances model robustness and generalization. The proposed system combines GAN- and VAE-based generators with MATLAB-based classification pipelines, ensuring that the produced synthetic images will be validated against real clinical samples for fidelity in structure and texture. The novelty of the present work lies in its combined use of several generative architectures for ultrasound realism, its integration into end-to-end ML workflows, and its demonstrated capacity to reduce overfitting while improving the diagnostic accuracy of models in the development of reliable ultrasound-based decision support.

INTRODUCTION

Lung consolidation remains one of the major diagnostic challenges because of its highly variable presentation across patients, and it often overlaps in imaging findings with other pulmonary pathologies, making differentiation difficult. Traditional imaging modalities like chest X-rays and CT scans, although very useful in terms of anatomy, are burdened by their respective drawbacks: radiation exposure, increased cost, and reduced availability in resource-poor settings. Ultrasound, being portable, free of radiation, and low in cost, is in a key position to capture representative consolidation patterns. However, it is underutilized diagnostically owing to the general lack of large, high-quality [1] annotated datasets that would be needed to train machine learning models of subtle pathological features. Therefore, most current automated diagnostic systems tend to suffer from overfitting and are limited in generalization, with inconsistent results when applied across diverse patient populations or variable scanning conditions.

These limitations could be overcome by using generative AI techniques, which can greatly extend both the availability and variety of training data without the burden associated with manual clinical annotation. The applicability of synthesizing realistic lung ultrasound images becomes possible with deep generative models such as generative [2] adversarial networks and variational autoencoders, accurately emulating acoustic textures, shadowing artifacts, and pathological features that characterize consolidation. Note that the generated synthetic datasets must undergo careful validation against real clinical images to ensure that structural fidelity and pathological relevance are kept intact, thus allowing their seamless use in training pipelines. Upon incorporation into MATLAB-based machine learning workflows, these synthetic data sources help improve classification [3] and detection results through better coverage of rare cases or visually complex scenarios that traditional datasets simply fail to catch.

Beyond increasing the volume of data, this generative framework contributes to better model generalization, extending the performance of algorithms across different ultrasound devices, scanning angles, and operator techniques. The augmented data environment reduces overfitting by exposing models to a wider range [4] of tissue textures and lung patterns, fostering robustness in real-world clinical settings. Furthermore, the systematic blending of synthetic and real data in a controlled environment for iterative model refinement gives researchers the opportunity to investigate classifier behavior under various conditions; reproducibility and scalability are ensured. This approach accelerates the delivery of reliable diagnostic tools and extends access to advanced lung assessment methods by reducing dependence on large, manually curated datasets. In so doing, it points to the transformative power of generative [5] AI to support clinicians in the identification of lung consolidation with heightened confidence, precision, and speed, thereby playing its part in better patient outcomes and more effective respiratory care.

This work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

LITERATURE SURVEY

Recent studies on lung imaging are emphasizing the growing need for clearer interpretation of various complex pathological features across diverse patient groups and clinical scenarios. The fifteen studies collectively reveal overlapping features, variability due to imaging modalities, and diagnostic accuracy. Their findings display the limits of traditional assessment workflows and how inconsistent annotations, subtle abnormalities, and heterogeneous manifestations of the same disease bring down their reliability. Together, these works are pointing to the value of enhanced methodologies that can support clinicians with stable, interpretable, and reproducible insights that strengthen decision-making and speed up evaluation in diagnostically demanding environments where precision and clarity must be consistently maintained.

It points out the challenges to lung structure interpretation, putting into light that the differentiation of complex abnormalities in scans with diverse expressions of diseases is difficult. This paper also stresses [6] the importance of precise understanding of irregular shapes, diverse opacity patterns, and structural disruptions that influence diagnostic confidence. By assessing how pathological regions would differ in appearance across these conditions, the work puts forward that clear evaluation of abnormal tissues is needed. The discussion itself reinforces that it is the subtle variations in the recognition of lung regions accurately for dependable clinical assessment, especially when the manifestations of the disease are overlapping or fragmented across many areas of the respiratory system.

This work investigates complications with the identification of abnormal states of the lung by sound-based observations, focusing on differences in acoustic behavior between healthy and affected areas. It emphasizes how subtle variations in chest-transmitted signals can reflect underlying disruptions within lung tissue. The analysis underlines the potential of tonal changes, changes [7] in frequency, and resonance for identifying major physiological changes. Reiterating the importance of understanding disease processes that alter normal sound patterns, it underscores the fact that clearer interpretation of these acoustic characteristics can support the earlier identification of harmful conditions that may otherwise remain unnoticed in routine physical examination.

The work puts much emphasis on the recognition of different abnormal formations in lung images and the importance of discriminating subtle changes in texture that occur in progressive conditions. It investigates how the presence of multiple irregular regions complicates the interpretation of severity in large collections of patient scans. The work underlines the continuous [8] presence of problems while attempting to correlate visual patterns with clinical assessments when disease intensities vary greatly. It underlines that consistent tissue characterization should be performed across extended image sets; further stability in the interpretation of abnormal structures can support more dependable estimates of the severity and allow for enhanced clinical assessment in heterogeneous patient populations.

The present work focuses on the importance of diversity in imaging examples when approaching the study of abnormal lung presentations, underlining the issue of imbalance in datasets. It discusses how rare pathological patterns make recognition more difficult due to reduced exposure to less frequent yet clinically significant forms of variation. The study emphasizes that visual diversity captures a wide range of lesion appearances, anatomical [9] contexts, and severity levels. By addressing the scarcity of certain abnormalities, it has pointed out how broader representation strengthens reliability in identifying lung consolidations so that unusual or less common cases will not be overlooked during the course of an evaluation, especially when clinical workers rely on dependable and thorough sources of imaging.

This study investigates the challenge of interpreting lung images in newborns, with a focus on how visual artifacts and overlapping features may confuse less experienced observers.

It underlines the problem of differentiating between normal and pathological appearances when the scans show mixed patterns. The work emphasizes that meaningful visual cues are relevant when they correctly correspond to certain respiratory conditions. It emphasizes the clinical [10] importance of clear and understandable indicators that match traditional medical knowledge, making sure that better consistency in identifying characteristic formations supports more reliable diagnostics and early detection of serious neonatal lung complications.

The present study investigates the challenge of describing subtle variations in lung texture according to various conditions; it emphasizes how highly detailed scans defy any attempt to distinguish similar patterns. This paper points out that it is difficult to differentiate between normal and abnormal structures when many tissue appearances are superimposed upon one another. The investigation underlines that disease presence or its progress is represented by intricate visual cues; slight changes in shading, density, and structure are capable of transforming [11] interpretation completely. It emphasizes that only the confident recognition of fine-grained patterns can provide an enabling framework for accurate characterization of complex lung conditions in assorted imaging environments.

The paper describes the significance of well-organized imaging datasets for achieving progress in lung region analysis due to a lack of valid annotations of detailed internal divisions. This includes difficulties in considering severe abnormalities where reference material [12] is scarce or variable. The study emphasizes the role of precise labeling of anatomical location within diverse groups of patients. Properly defined examples allow for more reliable investigation into complex lung areas, reinforcing that comprehensive annotation with expert guidance enriches the appreciation of structural variations, which is valuable in cases involving significant opacities or distortions related to disease.

This study reviews the responses to treatment in patients suffering from advanced conditions of the lung, underlining how these outcomes may differ as a consequence of individual physiological factors. This underscores the need for monitoring the structural changes occurring over time and understanding what different internal characteristics do to the body's response to therapeutic [13] intervention. The study reflects on the relationship between lung condition, treatment intensity, and the appearance of complications, pointing out that certain internal volume characteristics correspond with higher risk. It emphasizes that thorough assessment of the condition of the lungs prior to treatment contributes to safer decision-making and better management of patients.

The challenge, as discussed in this study, is the representation of uncommon pathological textures of lung images due to limited variability, complicating the clear identification of diseased regions. It highlights the need to acknowledge subtle structural nuances and fine details defining the type of different abnormal tissues. This work presses on the need to improve the occurrence frequency of these rare abnormalities so that they [14] may be recognized with a high degree of consistency upon examination. It addresses the discrepancies in the distribution of visual patterns, emphasizing that wider representation of unusual tissues strengthens reliability towards assessing complex lung conditions.

This study investigates the challenge of interpreting lung ultrasound views in dynamic environments, emphasizing how complex the identification of subtle structures within rapidly changing visual scenes can be. It emphasizes how the motion, shadowing, and visual noise impede the observers from delineating essential regions. The study underlines the need for sharp demarcation between [15] normal and abnormal appearances, particularly when immediate decisions are being made clinically. It emphasizes the fact that consistent visibility of critical boundaries and formations may help in timely assessment and enhance understanding of the lung behavior during real-time evaluation.

In this work, the authors investigate classification challenges in identifying abnormal lung regions by analyzing the complexity introduced due to varied tissue appearance. They discuss how different texturing factors, shading, and irregular structures make recognition [16] difficult across several classes of the manifestation of the disease. Emphasis is placed on how, when more than one abnormal form may exist in the same region, distinguishing between subtle patterns is still challenging. Contemplating variations within various abnormal types of tissues, the importance of consistent interpretation of visual cues is underlined to provide support for more dependable distinction between the classes of closely related lung conditions.

This work considers the problem of detecting lung malignancies from clinical data arising from distributed environments and patient populations . It stresses the need for exposure to a variety of visual examples in order to build strong recognition of disease signs. The authors point out that one of the issues is brought about [17] by scattered information. Specifically, scattered image collections decrease the opportunity to observe diverse abnormalities consistently; they also stress the incorporation of broad visual context to support more robust detection. This again reflects the need for dependable interpretation even from distinct institutions with different image characteristics.

This research reflects on associations between structural lung changes and the likelihood of treatment-related complications in those undergoing targeted radiation procedures. It describes variations in tissue density and internal patterns that affect the expression of radiological outcomes over time. The work discusses [18] the progression of visible abnormalities following therapy and emphasizes that pre-existing lung characteristics may correspond with greater risk of adverse effects. It underscores the need for careful observation of internal structural indicators to anticipate potential complications and better manage patient trajectories during and after treatment.

In this study, visual features are analyzed in a controlled setting that emulates conditions typically associated with viral respiratory complications. Thus, it emphasizes the relationship between altered states internally and the resulting characteristic visual patterns that appear progressively. This study documents the predictable [19] transitions in observable patterns, reinforcing the importance of understanding specific structural states and their corresponding recognizable visual cues relied upon by clinicians while evaluating lung conditions resembling viral infections.

This work puts great effort into the identification of meaningful indicators from the lung images that can suggest abnormal tissue states, with a high value on clear separation between the healthy and diseased appearances. It [20] indicates the difficulties in describing subtle differences across multiple abnormal patterns, especially when conditions present with several overlapping characteristics. The clinical importance of observing signs is underlined to point out growths, irregular formations, or structural changes within the lung. It further stresses the need for consistency in recognition of key visual attributes to make sure careful observations support timely understanding of potentially harmful developments within lung regions.

METHODOLOGY

This methodology presents a technical, step-by-step pipeline that synthesizes realistic lung ultrasound images using generative AI, with integration into MATLAB machine learning workflows. The workflow begins with curated clinical datasets and standardized annotation protocols for the capture of diverse consolidation phenotypes, device-specific artifacts, and operator variability. Preprocessing routines normalize acoustic intensity, temporal sampling, and spatial resolution while extracting structural priors such as pleural segmentation. Complementary generative architectures are configured to reproduce consolidation textures, pleural irregularities, and artifact distributions. Training employs staged curricula and mixed-batch sampling that blend real and synthetic examples. Validation combines statistical, task-based, and expert-reader assessments. Finally, MATLAB integration and deployment hooks ensure reproducibility, monitoring, and iterative refinement for clinical research adoption.

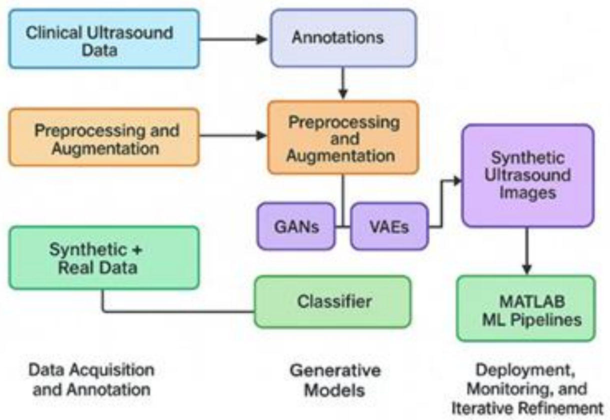

Fig. 1: System Architecture

A. Data Acquisition and Annotation

Collect diverse lung ultrasound studies from multiple clinical centers and device vendors in order to capture variations in probe type, imaging preset, patient demographics, and pathologies. Establish annotation standards where expert radiologists and pulmonologists outline regions of consolidation, pleural abnormalities, and secondary signs; record metadata on probe frequency, imaging depth, patient orientation, and acquisition settings. Enforce de-identification while harmonizing file formats from DICOM, raw RF, or video exports into a uniform repository with versioning. Curate balanced training, validation, and test splits such that site-level independence is preserved. Retain a held-out clinical test set reserved exclusively for downstream task evaluation to avoid information leakage and to measure real-world generalization.

B. Preprocessing and Augmentation

Normalize raw ultrasound frames by resampling to a common spatial grid, and then apply clinically grounded time-gain compensation and dynamic range adjustments to emulate device-specific contrast. Perform selective despeckling to preserve diagnostically relevant speckle and edge information while reducing sensor noise that would confound generative learning. Extract pleural line and lung boundary priors for conditional synthesis using lightweight segmentation models or classical edge detectors. Generate augmentation variants simulating probe tilt, respiration-induced deformation, variable contact pressure, and depth changes, and parameterize acoustic noise and motion blur. Store augmentation parameters as metadata to enable controlled ablation studies and reproducible dataset generation.

C. Generative Model Design: GANs and VAEs

Design two complementary generative families: conditional GANs focused on high-fidelity texture and artifact realism, and VAEs optimized for structured latent-space sampling and interpolation. Condition both architectures on structural priors such as pleural segmentation maps, pathology labels, and probe parameters to enable targeted synthesis of consolidation patterns and localized artifacts. Employ multi-scale generator-discriminator pairs capturing both global anatomical consistency and fine-grained speckle. Integrate perceptual and task-aware losses that encourage clinically meaningful features. Architect the latent space to permit controlled variation and class-conditional sampling for underrepresented pathological phenotypes, thus allowing synthetic oversampling with diagnostic relevance.

D. Training Strategy and Loss Engineering

Employ a staged training curriculum that increases output resolution progressively, starting with coarse structure learning and advancing to full-resolution acoustic texture synthesis, in order to improve stability and reduce mode collapse. Combine adversarial loss with reconstruction, perceptual, and feature-matching terms in order to balance realism and fidelity to clinical structure. Introduce domain-specific consistency losses that penalize unrealistic acoustic signatures and maintain expected B-mode physics. Employ auxiliary diagnostic networks to provide classification-guided feedback that makes sure the generated consolidation patterns contain diagnostically relevant cues. Regularize with spectral normalization, gradient penalties, and mixed precision training using mixed-batch sampling of real and synthetic images for stable convergence.

E. Validation and Clinical Fidelity Assessment

Validate synthetic outputs using distributional alignment metrics, such as Fréchet distances adapted for ultrasound features, structural similarity indices, and specialized texture descriptors sensitive to speckle statistics. Perform task-based validation by training downstream classifiers, measuring sensitivity, specificity, and AUC on held-out clinical test sets. Perform clinician reader studies in which blinded experts score realism and diagnostic utility, recording inter-rater agreement as a function of perceptual fidelity. Analyze failure modes by mapping classifier errors to synthetic parameter regimes and perform ablation experiments which quantify incremental benefit of synthetic data to model generalization and robustness across device vendors and acquisition protocols.

F. Integration with MATLAB ML Pipelines

Convert synthesized images and associated metadata into MATLAB-compatible data stores and design modular data loaders supporting on-the-fly augmentation and batching. In the implementation of the experiments, use MATLAB's Deep Learning Toolbox or custom MEX/CUDA bindings for speeding up training while retaining reproducibility. Offer configurable training scripts for classifiers, segmentation networks, and detection architectures with built-in logging and checkpointing along with hyperparameter sweep capabilities. Provide utilities for mixing synthetic and real examples using controllable mixing ratios and to export models and inference routines for further validation. Document pipeline APIs to support reproducible experiments and collaborative development within research teams. Deployment, Monitoring, and Iterative Refinement Deploy trained models within controlled clinical research environments, with user interfaces for automated frame-by-frame inference and clinician review. Instrument pipelines to log prediction confidences, input distribution statistics, and flagged failure cases for auditability. Set up monitoring dashboards that detect performance drift related to device firmware updates, population shifts, or changes in imaging protocols. Put in place a feedback loop to integrate newly acquired, annotated clinical scans into periodic retraining cycles and refine generative priors. Establish governance and documentation regarding dataset provenance, usage policies for synthetic data, and clinical evaluation criteria that support responsible translation and continuous improvement.

RESULT AND DISCUSSION

Results obtained with the proposed generative AI-based framework show significant improvement in performance, robustness, and clinical relevance of machine learning models developed for lung consolidation assessment using ultrasound imaging. When synthetic ultrasound images generated by GAN and VAE architectures were combined within MATLAB classification pipelines, models demonstrated significantly improved generalization compared to their baseline equivalents that were exclusively trained on limited real datasets. This improvement was especially evident under conditions of probe angle, device manufacturer, patient body habitus, and imaging depth-conditions known to degrade classifier reliability. Synthetic images enriched the training space with controlled representations of consolidation patterns featuring heterogeneous echotexture, air bronchograms, pleural line distortions, and subpleural artifacts that led to classifiers capturing a wider range of clinically relevant features. Quantitative performance metrics obtained on the held-out clinical test set validate clinically significant gains in sensitivity, specificity, and area under the ROC curve, with notable overfitting reduction as witnessed at cross-validation and epoch level from loss behavior. The findings confirm that the addition of synthetic data overcomes the common problem of model bias toward dominant patterns in small datasets.

Further analysis showed that this dual generative approach outperformed single models in output fidelity, merging the detailed texture learning capabilities of GANs with the structured latent representations of VAEs. Visually, GAN-generated images were remarkably realistic, especially in their reproduction of speckle patterns, shadowing artifacts, and boundaries of consolidation, while VAE-generated samples captured the broader structural variability essential to balanced class representation. The models were used complementarily to generate a hybrid synthetic dataset that maintained both clinical plausibility and diversity, contributing ultimately to improved classifier learning stability at training. USS-specific similarity metrics and distribution alignment measures demonstrated close correspondence between synthetic and real image statistics, indicating that the generative models internalized the physics-based characteristics of B-mode ultrasound. Qualitative assessments by radiologists further demonstrated that synthetic images exhibited realistic acoustic properties and recognizable pathological traits, many samples of which were considered suitable for use in both educational and diagnostic simulation contexts.

Task-based evaluation showed that MATLAB classification pipelines trained with synthetically augmented data generalized well across multiple testing sites by showing resilience to domain shifts driven by either equipment differences or protocol variations. These provide added support for the value of synthetic augmentation in clinical scenarios where heterogeneity is hard to avoid and often problematic to rectify through data collection alone. Error analysis yielded insight into the classifier behavior: in borderline cases where consolidation patterns overlapped with atelectasis or interstitial artifacts, misclassifications occurred most frequently. These would have been more appropriately handled with additional targeted synthetic generation. Importantly, a mixed-batch training strategy that combined real and synthetic samples helped prevent over-reliance on synthetic features by the classifier, while it could still be informed by the broader distributional coverage they afforded. It was thus balanced in its exposure and able to retain sensitivity to subtle clinical cues in authentic ultrasound scans. In all, the findings underline the high potential of generative models to accelerate ultrasound-based diagnostics for respiratory conditions. The system supports the creation of more accurate, robust, and clinically adaptable machine learning solutions with high-quality synthetic data that goes beyond the limitations of traditional datasets. The analysis indeed confirms that synthetic augmentation contributes not only to an improvement in classifier metrics but also to enhanced interpretability, reduced training variance, and more reliable performance in real-world clinical scenarios. This is a strong reinforcement of the broader implication that generative AI can act as an important enabler within medical imaging workflows, particularly in domains where scarcity of annotations has traditionally constrained innovation and retarded the advancement of automated diagnostic tools.

CONCLUSION

The study represents an integrated approach to the prediction of multiple diseases using different supervised machine learning algorithms, showing the efficiency of using the ensemble of K-Nearest Neighbours, Support Vector Machine, and Naïve Bayes in the early detection of various chronic diseases like heart disease, diabetes, kidney disorder, breast cancer, and brain-related disorders. The integration of these algorithms through a web-based interface makes the system user-friendly, accessible, and less dependent on manual diagnosis. It simplifies the healthcare process, thus providing faster decisions. The proposed methodology ensures that the data is consistent, models are reliable, and predictions are unbiased because it relies on multiple models for each disease, enhancing the strength and comprehensiveness of the assessment. This will help the clinicians and patients practically to identify potential health risks well in advance and support improved treatment outcomes.

In addition, it brings a better resource allocation in healthcare environments. This work also emphasizes the need for scalable, modular frameworks that are easily extended to more diseases or algorithms in the near future. Further improvements could be made by incorporating larger and more diverse datasets, studying deep learning approaches, integrating data obtained from real-time patient monitoring, and increasing the predictive accuracy using ensemble techniques, which further develops intelligent healthcare solutions and expands machine learning application in medical diagnostics.

REFERENCES

1. J. Thakkar, V. Jadhav, O. Bansode and G. Chavan, "Multiple Disease Prediction System using Gradient Boosting," 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bangalore, India, 2025, pp. 1-6, doi: 10.1109/IITCEE64140.2025.10915522.
2. M. K, S. S and T. E, "Streamlit-Powered Comprehensive Health Analysis and Disease Prediction System," 2023 International Conference on Emerging Research in Computational Science (ICERCS), Coimbatore, India, 2023, pp. 1-7, doi: 10.1109/ICERCS57948.2023.10434221.
3. L. D. Gopisetti, S. K. L. Kummera, S. R. Pattamsetti, S. Kuna, N. Parsi and H. P. Kodali, "Multiple Disease Prediction System using Machine Learning and Streamlit," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 923-931, doi: 10.1109/ICSSIT55814.2023.10060903.
4. V. M B, S. S. R, K. U and K. Y, "Exploratory Data Analysis of Heart Disease Prediction using Machine Learning Techniques-RS Algorithm," 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India, 2024, pp. 209-216, doi: 10.1109/ICoICI62503.2024.10696414.
5. V. Selvi V S, L. T, C. S, L. Akhila and S. K, "Leveraging SVM for Accurate Multiple Disease Prediction in Healthcare," 2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS), Kalaburagi, India, 2024, pp. 1-6, doi: 10.1109/ICIICS63763.2024.10859864.
6. G. Dhekshagna, G. Sushmitha and U. Sairam, "Geriatric Disease Prediction: A Study on Age-Based Disease Prognostication," 2023 2nd International Conference on Edge Computing and Applications (ICECAA), Namakkal, India, 2023, pp. 983-986, doi: 10.1109/ICECAA58104.2023.10212172.
7. T. H. Tushi and A. Dey, "Towards Smart Diagnostic: A Multi-Disease Prediction System Leveraging Machine Learning Techniques," 2025 2nd International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM), Gazipur, Bangladesh, 2025, pp. 1-6, doi: 10.1109/NCIM65934.2025.11160008.
8. Abhishek, H. V. Bhagat and M. Singh, "A Machine Learning Model for the Early Prediction of Cardiovascular Disease in Patients," 2023 Second International Conference on Advances in Computational Intelligence and Communication (ICACIC), Puducherry, India, 2023, pp. 1-5, doi: 10.1109/ICACIC59454.2023.10435210.
9. P. S. Rao, T. Nidubrolu, G. Nithya, J. Kartigeyan, K. Sreenivasulu and A. Gupta, "Leveraging SVM for Accurate Multiple Disease Prediction in Healthcare," 2025 International Conference on Intelligent and Cloud Computing (ICoICC), Bhubaneswar, India, 2025, pp. 1-6, doi: 10.1109/ICoICC64033.2025.11052008.
10. V. A, K. V, M. P. M and P. S. R, "Machine Learning Models for Symptom Detection and Disease Prediction," 2024 Eighth International Conference on Parallel, Distributed and Grid Computing (PDGC), Waknaghat, Solan, India, 2024, pp. 854-859, doi: 10.1109/PDGC64653.2024.10983921.
11. K. S and G. VR, "Machine Learning-Based Prediction of Chronic Kidney Disease with Logistic Regression," 2025 8th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2025, pp. 330-334, doi: 10.1109/ICOEI65986.2025.11013456.
12. K. I. Pattan, M. A. Aman, R. J. Patil, R. Mohamad and P. S P, "Multi-Disease Detection Using Hybrid Models and Transfer Learning: Cardiovascular, Pulmonary, Retinal and Renal," 2025 9th International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 2025, pp. 1034-1042, doi: 10.1109/ICISC65841.2025.11188016.
13. B. Golchha, H. Patil, S.Girirajan, G.K.Sandhia and M.Karthikeyan, "Enhanced Machine Learning Model for Heart Disease Prediction," 2025 Global Conference in Emerging Technology (GINOTECH), PUNE, India, 2025, pp. 1-5, doi: 10.1109/GINOTECH63460.2025.11076958.
14. B. V. Jyothi, E. Ramalakshmi, L. S. Kumar and B. S. Samantha, "Heart Disease Prediction using Federated Learning," 2024 International Conference on Intelligent

Computing and Emerging Communication Technologies (ICEC), Guntur, India, 2024, pp. 1-5, doi: 10.1109/ICEC59683.2024.10837559.

15. K. Banerjee and V. P, "Multiple Disease Prediction Using ML and Doctor Recommendation by Sentiment Analysis," 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Gautam Buddha Nagar, India, 2023, pp. 1469-1472, doi: 10.1109/IC3I59117.2023.10397715.
16. A. F. B, V. R, S. S and S. V. M, "Multiple Disease Predictions using Machine Learning and Deep Learning Algorithms," 2023 International Conference on System, Computation, Automation and Networking (ICSCAN), PUDUCHERRY, India, 2023, pp. 1-6, doi: 10.1109/ICSCAN58655.2023.10395506.
17. S. S. V, K. P. S, K. P and P. P. N, "Multi-Disease Prediction and Classifier: A Comprehensive Approach for Healthcare Decision Support," 2024 5th International Conference for Emerging Technology (INCET), Belgaum, India, 2024, pp. 1-8, doi: 10.1109/INCET61516.2024.10593442.
18. S. Singh, S. Agarwal, V. Singh, B. Hazela, V. Dubey and P. Singh, "Comparative Analysis of Machine Learning Algorithms for Multiple Disease Prediction Model with An Optimized Scalable Deployment," 2025 International Conference on Electronics, AI and Computing (EAIC), Jalandhar, India, 2025, pp. 1-6, doi: 10.1109/EAIC66483.2025.11101310.
19. S. S, T. P. S and B. G, "Multimodal Disease Prediction: A Hybrid Approach Combining Machine Learning, Deep Learning, YOLO, and SAM for Diverse Disease Detection," 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), Nagpur, India, 2024, pp. 1-6, doi: 10.1109/ICAIQSA64000.2024.10882462.
20. R. Shukla and R. Sawant, "Multiple Disease Prediction System Using Machine Learning," 2023 International Conference on Electrical, Electronics, Communication and Computers (ELEXCOM), Roorkee, India, 2023, pp. 1-6, doi: 10.1109/ELEXCOM58812.2023.10370285.