International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 1, pp.153-160, January 2026.
www.ijersem.com eISSN- 3107-9075

Multi-disease Detection System Using Machine Learning

[1]B. Himabindu, [2]A Chaithanya, [3]Y Kumarnadh, [4]T.B. Durga Prasad, [5]A Kumarsrinivas, [6]Lakshmipathi

Department of CSE, Siddartha Institute of Science and Technology, Puttur, India.

[1]himabindubukkapatnam@gmail.com, [2]chaituarkonam@gmail.com, [3]kumarnadh2005@gmail.com, [4]durgaprasanthtb@gmail.com, [5]kumarsrinivas187@gmail.com, [6]umamurali06077@gmail.com

Abstract: Machine learning has the potential to revolutionize healthcare because to the growing availability of medical data and the growing demand for quick, precise diagnosis. The Multi-Disease Detection System presented in this research uses machine learning algorithms to automatically detect and categorize various diseases based on medical imagery and patient data. To guarantee excellent accuracy and dependability across a variety of illness categories, the system incorporates sophisticated preprocessing approaches, feature extraction, and optimal classification models. The program may provide early and reliable illness predictions by identifying intricate patterns and connections in medical records. This helps physicians make decisions more quickly. Additionally, the system has a user-friendly interface that allows users to submit medical data and receive immediate diagnostic results. The goal of this research is to lessen the burden associated with manual diagnostics, improve early detection and support scalable, AI-powered medical solutions.

Keywords: Multi-Disease Detection, Machine Learning, Healthcare Analytics, Medical Data Classification, Disease Prediction.

1 Introduction

The growing digitalization of medical data and developments in artificial intelligence are driving an unprecedented revolution in the healthcare sector. Large volumes of patient data are produced by modern hospitals and diagnostic facilities, including sensor-based physiological measurements, laboratory test results, electronic health records, and medical imaging data. The sheer volume and complexity of medical data make manual analysis more ineffective and prone to mistake, even if this data has immense potential to improve diagnostic and treatment results.

Accurate illness One of the most important components of providing healthcare is diagnosis. Early diagnosis lowers mortality, increases treatment success rates, and lowers medical expenses. However, manual clinical evidence interpretation and physician experience play a major role in traditional diagnostic procedures. These techniques are frequently laborious and prone to human constraints including weariness, cognitive bias, and clinical experience variability. Diagnosis is further complicated by the fact that many individuals have symptoms that are similar to those of several different illnesses. Large-scale medical information may be analyzed by machine learning (ML), a potent technology that can uncover hidden patterns that are challenging for humans to recognize.

ML algorithms are able to produce reliable diagnostic predictions, learn from past data, and adjust to new inputs. Because of these characteristics, machine learning is very. The majority of ML-based diagnostic systems now in use concentrate on diagnosing a single illness at a time, such as cancer, diabetes, or heart disease. Despite their effectiveness, these methods may not accurately represent actual clinical situations in which patients may be at risk for several illnesses at once. This constraint drives the creation of a Multi Disease Detection System, which can diagnose several illnesses inside a single framework and analyze patient data holistically. This research suggests a machine learning-based multi-disease detection system that combines improved preprocessing, feature extraction, and optimal classification models with clinical data and medical imaging. The system seeks to lessen manual labor, let physicians make decisions more quickly and accurately, and provide scalable, AI-driven healthcare solutions.

2 Literature Review

Early diagnostic systems relied on rule-based expert systems where medical knowledge was encoded as predefined rules. Although effective for specific conditions, these systems lacked adaptability and failed to generalize across diverse patient populations. Manual diagnosis remains dependent on physician experience and is susceptible to inconsistency. Machine learning algorithms such as Logistic Regression, Decision Trees, Support Vector Machines, and Naïve Bayes have been widely applied for detecting individual diseases.

Numerous studies report improved accuracy compared to manual diagnosis, particularly for diabetes and cardiovascular disease prediction. However, these systems typically operate in isolation and cannot handle multi-disease complexity. Recent research has explored multi-class and multi-label classification techniques for disease prediction. These approaches allow a single model to predict multiple conditions, reflecting real-world healthcare needs. Ensemble learning and hybrid models have shown promise in improving robustness and generalization.

Combining structured clinical data with unstructured medical images significantly improves diagnostic accuracy. CNN-based image analysis enables automatic feature extraction from X-rays, MRIs, and CT scans, while clinical attributes provide contextual disease indicators. Key challenges include data heterogeneity, class imbalance, lack of interpretability, limited dataset size, and poor real-world validation. These limitations motivate the proposed unified multi-disease detection framework.

3 Disease Characteristics and Data Attributes for Automated Detection

A Multi Disease Detection System relies heavily on the quality, diversity, and relevance of the data attributes used for learning and prediction. Diseases manifest through a combination of demographic patterns, clinical symptoms, laboratory abnormalities, imaging findings, and biomarker variations. Effectively capturing these characteristics enables machine learning models to learn meaningful patterns and relationships that support accurate and early disease detection. This section discusses the key categories of data attributes used in the proposed system and their role in automated diagnosis.

3.1 Clinical Parameters and Patient Demographics

Clinical parameters and patient demographic information form the foundational layer of disease prediction. Attributes such as age, gender, body mass index (BMI), lifestyle habits, and family medical history provide essential baseline indicators of disease susceptibility. Many chronic diseases exhibit strong demographic trends; for example, cardiovascular diseases are more prevalent in older populations, while diabetes risk increases with higher BMI and genetic predisposition. Age plays a critical role in determining disease risk, progression rate, and severity.

Gender-specific differences influence the prevalence of conditions such as heart disease, osteoporosis, and certain cancers. BMI reflects metabolic health and is closely associated with obesity-related disorders, including diabetes, hypertension, and cardiovascular disease. Family history provides genetic context, allowing the system to account for inherited risk factors. In the proposed system, demographic data improves model personalization, enabling predictions to be tailored to individual patient profiles rather than relying solely on generalized population trends. These features help machine learning models establish baseline risk levels and improve predictive accuracy when combined with clinical and laboratory data.

3.2 Laboratory Test Features

Laboratory test results offer quantitative and objective measures of a patient’s physiological condition and are among the most informative features for disease detection. Parameters such as blood glucose levels, HbA1c, cholesterol profiles (LDL, HDL, triglycerides), liver enzymes (ALT, AST), kidney function markers (creatinine, urea), and complete blood count values are widely used in clinical diagnosis. Abnormal laboratory values often serve as early indicators of disease before symptoms become clinically apparent. For instance, elevated blood glucose and HbA1c levels are strong predictors of diabetes, while abnormal cholesterol levels indicate cardiovascular risk. Liver and kidney function tests help detect organ dysfunction and chronic disease progression. Machine learning models leverage these numerical features to identify subtle deviations from normal ranges and learn complex nonlinear relationships between laboratory parameters and disease outcomes. When combined across multiple tests, laboratory features significantly enhance the system’s ability to differentiate between diseases with overlapping symptoms.

3.3 Medical Imaging Features

Medical imaging data provides crucial visual evidence of structural and functional abnormalities that may not be captured through clinical or laboratory tests alone. Imaging modalities such as X-rays, MRI scans, CT scans, and ultrasound images are widely used for diagnosing conditions including tumors, organ damage, neurological disorders, and pulmonary diseases. In the proposed system, Convolutional Neural Networks (CNNs) are employed to automatically extract imaging features such as shape, texture, intensity patterns, and spatial relationships. These features enable the detection of anomalies such as lesions, masses, tissue degeneration, or abnormal organ structures. Imaging features complement structured data by offering high-dimensional visual information. For example, a patient’s laboratory values may indicate abnormality, while imaging data can localize and characterize the underlying pathology. Integrating imaging features with clinical data allows the system to achieve a more comprehensive and accurate disease assessment.

International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 1, pp.153-160, January 2026.
www.ijersem.com eISSN- 3107-9075

3.4 Disease-Specific Biomarkers

Disease-specific biomarkers play a critical role in distinguishing between different disease categories. Biomarkers include biochemical indicators, genetic markers, protein levels, and hormone concentrations that are strongly associated with specific conditions. For example, elevated troponin levels indicate cardiac injury, while tumor markers such as PSA or CA-125 are linked to certain cancers. Incorporating biomarker data allows the system to move beyond general symptom-based classification toward precision diagnosis. Biomarkers provide high discriminatory power, enabling machine learning models to differentiate between diseases that may share common clinical features. The proposed framework integrates biomarker information as specialized input features, improving classification confidence and reducing false positives. This is particularly valuable in multi-disease detection scenarios where accurate disease differentiation is essential for appropriate treatment planning.

3.5 Feature Correlation and Disease Interdependency

Diseases rarely occur in isolation; many conditions share common risk factors, symptoms, and biological pathways. For example, diabetes, hypertension, and cardiovascular disease often coexist and influence one another. Machine learning models excel at identifying such feature correlations and disease interdependencies that may not be explicitly defined by clinicians. By analyzing multidimensional data, the proposed system learns how combinations of features contribute to multiple disease outcomes simultaneously. This enables multi-class or multi-label prediction, where a patient may be identified as being at risk for more than one condition. Understanding feature correlations also helps improve interpretability and clinical relevance. The system can highlight which combinations of demographic, laboratory, and imaging features contribute most strongly to specific disease predictions, supporting informed decision-making.

3.6 Data Quality and Variability

The reliability of any machine learning–based diagnostic system depends heavily on data quality. Medical datasets often contain missing values, noisy measurements, inconsistent records, and class imbalance, which can negatively affect model performance if not properly addressed. The proposed system incorporates robust preprocessing techniques to handle these challenges. Missing values are managed through imputation strategies, noisy data is filtered through normalization and outlier detection, and categorical variables are encoded consistently. Data variability arising from different hospitals, diagnostic equipment, and measurement protocols is mitigated through standardization. By ensuring high data integrity and consistency, the system improves learning stability, reduces bias, and enhances generalization across diverse patient populations. Effective data handling is essential for deploying the system in real-world healthcare environments.

4 SYSTEM DESIGN

The implementation of the proposed Multi Disease Detection System Using Machine Learning is designed to ensure accuracy, scalability, and clinical relevance. The system adopts a modular and layered architecture that allows efficient handling of heterogeneous medical data, seamless integration of multiple machine learning models, and reliable delivery of diagnostic results. Each module performs a distinct function while contributing to the overall disease detection workflow.

4.1 Overall System Architecture

The proposed system follows a modular architecture that consists of several interconnected layers, including data input, preprocessing, feature extraction, classification, and output generation. This layered design enhances flexibility, maintainability, and scalability, allowing the system to be easily extended to additional diseases or data sources in the future. The data input layer accepts patient information in multiple formats, including structured clinical records, laboratory test values, and medical images such as X-rays or MRI scans. These inputs are validated and standardized before entering the processing pipeline. The modular design ensures that each type of data is processed through appropriate techniques tailored to its characteristics. The processing pipeline enables smooth data flow between modules, ensuring minimal latency and consistent handling of patient records. This architecture supports both batch processing for offline analysis and real-time inference for immediate diagnostic support. By separating concerns across modules, the system achieves robustness and adaptability suitable for real-world healthcare applications. Fig. 1 show the flow diagram of the proposed method.

4.2 Data Preprocessing Module

Data preprocessing is a critical component of the proposed system, as medical datasets often contain missing values, noise, and inconsistencies. The preprocessing module ensures that all inputs are transformed into a clean, standardized, and machine-learning-ready format. For structured clinical and laboratory data, preprocessing steps include data cleaning, normalization, and encoding. Missing values are handled using appropriate imputation techniques, while numerical features are normalized to maintain consistent scales. Categorical variables such as gender or symptom categories are encoded using suitable encoding schemes.

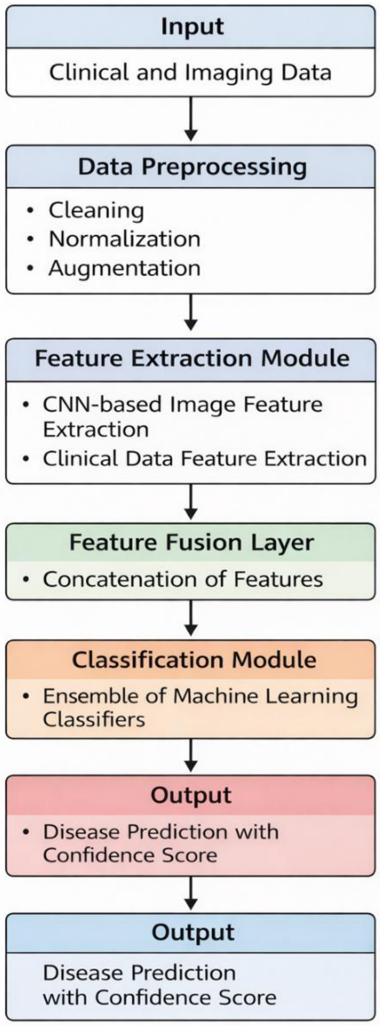

Fig. 1. Flow Diagram of the proposed method

For medical imaging data, preprocessing involves image resizing, intensity normalization, noise reduction, and enhancement techniques. These steps improve image quality and ensure compatibility with CNN-based models. Data augmentation techniques such as rotation, flipping, and scaling are optionally applied to increase dataset diversity and improve model generalization. By ensuring consistent and high-quality inputs, the preprocessing module significantly improves learning stability and prediction accuracy across all disease categories.

4.3 Feature Extraction and Selection

Feature extraction and selection play a central role in identifying disease-relevant patterns from high-dimensional medical data. The proposed system employs a hybrid approach that combines statistical feature extraction for structured data with CNN-based feature extraction for medical images. For clinical and laboratory data, statistical methods are used to derive meaningful features such as mean values, trends, and ratios that reflect physiological conditions. Feature selection techniques reduce dimensionality by eliminating redundant or irrelevant attributes, improving model efficiency and interpretability. For imaging data, CNNs automatically extract hierarchical features such as edges, textures, shapes, and spatial relationships. These learned features capture complex visual patterns associated with disease manifestations. By integrating extracted features from multiple data sources, the system creates a comprehensive feature representation that enhances disease discrimination.

4.4 Machine Learning Models

The system incorporates multiple machine learning models to ensure robust and reliable disease prediction. Algorithms such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and Neural Networks are trained and evaluated using the extracted feature sets. Logistic Regression provides a baseline model with high interpretability, allowing insights into feature contributions. SVM is effective in handling high-dimensional data and complex decision boundaries. Random Forest models offer strong generalization and resistance to overfitting while providing feature importance measures.

Neural Networks capture nonlinear relationships and complex feature interactions that are difficult to model using traditional algorithms. By evaluating multiple models, the system selects or combines the most effective approaches for accurate multi-disease detection.

4.5 Multi-Disease Classification Strategy

The proposed system employs a multi-class and ensemble-based classification strategy to support simultaneous prediction of multiple diseases. Instead of limiting predictions to a single condition, the system is designed to identify multiple disease categories based on learned feature patterns. Ensemble learning techniques combine predictions from multiple models to improve accuracy and reduce bias. This strategy enhances reliability, particularly in cases where diseases exhibit overlapping symptoms or shared risk factors. The classification framework supports early detection by identifying disease risks even when symptoms are subtle. The multi-disease strategy reflects real-world clinical scenarios and supports comprehensive diagnostic decision-making.

4.6 User Interface and Output Module

The user interface serves as the interaction layer between healthcare professionals and the diagnostic system. It is designed to be intuitive, user-friendly, and accessible to non-technical users. Users can upload patient clinical data and medical images through the interface. The system processes the input data and displays diagnostic results, including predicted diseases, confidence scores, and summary insights. Confidence scores help clinicians assess prediction reliability and support informed decision-making. By providing rapid and consistent outputs, the interface reduces manual diagnostic workload and enhances clinical efficiency. The output module is designed to integrate seamlessly with existing healthcare systems, enabling practical deployment in real-world environments.

5 COMPARATIVE EVALUATION AND DISCUSSION

The evaluation of a multi-disease detection system is essential to validate its diagnostic reliability, robustness, and clinical applicability. In this paper, a comprehensive comparative evaluation was conducted to assess the performance of different machine learning models across multiple disease categories. The evaluation focuses on standard medical classification metrics and provides a detailed discussion of the results in comparison with traditional diagnostic approaches.

5.1 Disease Detection Performance Comparison

To ensure an objective comparison, the machine learning models were evaluated using widely accepted performance metrics, including accuracy, precision, recall (sensitivity), and F1-score. These metrics provide a balanced assessment of the system's ability to correctly identify diseased and non-diseased cases across multiple disease categories. Accuracy measures the overall correctness of predictions, while precision evaluates the proportion of correctly identified disease cases among all predicted positives. Recall is particularly critical in healthcare applications, as it measures the system's ability to correctly identify actual disease cases, minimizing false negatives. The F1-score balances precision and recall, offering a comprehensive indicator of classification reliability.

Comparative analysis across disease categories revealed that ensemble-based models and neural networks consistently achieved higher accuracy and recall compared to simpler models. Random Forest and Neural Network models demonstrated strong performance due to their ability to capture nonlinear relationships and complex feature interactions. Logistic Regression provided interpretable baseline results, while SVM performed effectively on high-dimensional feature sets.

5.2 Discussion of Classification Results

The classification results demonstrate that the proposed multi-disease detection framework significantly improves early disease detection and prediction consistency. Models trained using comprehensive feature sets, including demographic data, laboratory parameters, and imaging features, outperformed those relying on limited data sources. One of the key observations was the system's ability to detect disease risk at early stages, even when clinical symptoms were mild or overlapping. This capability is particularly valuable in preventive healthcare, where early intervention can significantly improve patient outcomes. The consistency of predictions across repeated evaluations indicates model stability and reliability. Compared to traditional diagnostic methods, the machine learning-based system reduced variability and improved diagnostic confidence. The use of ensemble strategies further enhanced robustness by mitigating the weaknesses of individual models.

5.3 Factors Affecting Detection Accuracy

Several factors were identified as having a significant impact on disease detection accuracy. Dataset quality emerged as a critical factor, as noisy or incomplete data can lead to inaccurate predictions. Robust preprocessing and imputation strategies were essential in mitigating these issues. Feature selection and representation also played a major role in performance.

International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 1, pp.153-160, January 2026.
www.ijersem.com eISSN- 3107-9075

Including relevant laboratory parameters, biomarkers, and imaging features improved disease discrimination, while redundant features negatively affected model efficiency. The choice of model architecture and complexity influenced the system's ability to generalize across diverse patient populations. Class imbalance across disease categories posed challenges, particularly for rare conditions. Addressing imbalance through resampling techniques and ensemble learning improved classification fairness and sensitivity.

5.4 Manual Diagnosis vs Machine Learning-Based Detection

Traditional manual diagnosis relies heavily on clinician experience and subjective interpretation, which can lead to variability and delays, especially in high-volume healthcare settings. Manual processes are also limited in their ability to simultaneously analyze large numbers of features and disease interactions. In contrast, the proposed machine learning–based detection system offers speed, scalability, and consistency. Once trained, the system can process large datasets rapidly and apply uniform diagnostic criteria across all cases. This reduces diagnostic workload, minimizes human error, and supports clinicians in making informed decisions. Rather than replacing medical professionals, the system functions as a computer-aided diagnosis (CAD) tool, enhancing clinical efficiency and accuracy. The comparative evaluation highlights the advantages of ML-based detection in supporting modern, data-driven healthcare delivery.

6 RESULTS

Fig. 2 illustrates the output generated by the proposed multi-disease detection system for a representative patient input. The system processes clinical parameters and, where applicable, medical imaging data to predict the most likely disease category along with an associated confidence score. This demonstrates the practical usability of the system in supporting clinical decision-making by providing clear and interpretable diagnostic results.

Fig. 3 presents a comparative performance analysis of different machine learning models used in the study. The comparison highlights that ensemble-based models and neural networks achieve higher accuracy and recall compared to traditional classifiers. Improved recall is particularly important in healthcare applications, as it indicates the system's ability to correctly identify diseased cases while minimizing false negatives. The results confirm that integrating multiple feature types and robust classifiers enhances overall diagnostic reliability. These visual results complement the quantitative evaluation and validate the effectiveness of the proposed system for early and accurate multi-disease detection.

Fig. 2. Sample output of the proposed multi-disease detection system showing predicted disease category along with confidence score.

International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 1, pp.153-160, January 2026.
www.ijersem.com eISSN- 3107-9075

Fig. 3. Performance comparison of machine learning models for multi-disease detection based on accuracy and recall metrics.

7 CONCLUSIONS

There is an urgent need for sophisticated, automated diagnostic systems that can assist medical personnel in providing prompt and correct care due to the fast expansion of medical data and the growing complexity of illness diagnosis. The Multi Disease Detection System Using Machine Learning, which is intended to automatically evaluate patient clinical data and medical photographs in order to identify and categorize numerous illnesses inside a single framework, was successfully demonstrated in this research. The suggested solution illustrates the revolutionary potential of machine learning in contemporary healthcare by solving the drawbacks of conventional, human diagnostic techniques. To guarantee accurate and consistent illness diagnosis across a variety of disease categories, the system incorporates sophisticated data preprocessing, feature extraction, and improved machine learning models. The framework offers a thorough and all-encompassing perspective of patient health by integrating demographic data, laboratory test results, biomarkers, and medical imaging characteristics. The system may identify intricate illness patterns and connections that are frequently challenging to find using traditional diagnostic techniques because to this multi-modal data integration.

The suggested system's capacity to facilitate early illness identification is one of its main advantages. The model successfully reduces false negatives, which is crucial in clinical situations when a delayed diagnosis might have dire repercussions. High recall and sensitivity across illness categories show this. Clinicians may start prompt treatments, improving patient outcomes and lowering long-term healthcare expenditures, thanks to the system's early detection of illness risk. The research admits certain limitations despite its great performance, including the need for comprehensive real-world clinical validation, class imbalance, and reliance on dataset quality. These difficulties offer chances for future improvements, such as the incorporation of explainable AI methods, real-time deployment on edge devices, and cooperation with medical facilities for extensive validation. To sum up, the suggested Multi Disease Detection System Using Machine Learning is an important step toward data-driven, intelligent, and scalable healthcare solutions. The system significantly advances AI-powered medical diagnostics and opens the door to more effective, individualized, and preventive healthcare delivery by decreasing the workload associated with manual diagnostics, improving early detection, and providing clinicians with reliable and consistent predictions.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

LICENSING

References

[1] N. Chowdhury, U. K. Das, S. Sazzad, A. Chowdhury, and P. Das, "Multimodal approach for early diagnosis of Parkinson's disease using PET imaging, tremor detection, and machine learning," *Psychiatry Research Neuroimaging*, vol. 353, p. 112063, Sep. 2025, doi: 10.1016/j.pscychresns.2025.112063.

[2] R. Nigam, K. K. Shukla, A. Birah, M. K. Khokhar, and B. K. Bhattacharya, "Integrating ground-based spectral reflectance and machine learning for Cotton Leaf Curl Virus Disease (CLCuD) detection in cotton crop," *Advances in Space Research*, vol. 76, no. 9, pp. 5126–5145, Aug. 2025, doi: 10.1016/j.asr.2025.08.019.

[3] X. Wang *et al.*, "Methodological innovation in chiral sensing with machine learning and multi-modal signal integration for tryptophan," *Chemical Engineering Journal*, vol. 526, p. 170926, Nov. 2025, doi: 10.1016/j.cej.2025.170926.

[4] M. Majdalawieh, C. Martins, M. Radi, M. Alaraj, and S. Khan, "Precision agriculture in the age of AI: A systematic review of machine learning methods for crop disease detection," *Smart Agricultural Technology*, vol. 12, p. 101491, Oct. 2025, doi: 10.1016/j.atech.2025.101491.

[5] R. Bhattarai and P. Rahimzadeh-Bajgiran, "Optimizing forest defoliation detection using remote sensing data: a multi–resolution approach using machine learning algorithms," *Trees Forests and People*, vol. 22, p. 101009, Sep. 2025, doi: 10.1016/j.tfp.2025.101009.

[6] H. Ali *et al.*, "Intelligent machine learning-based multi-model fusion monitoring: application to industrial physio-chemical systems," *Control Engineering Practice*, vol. 162, p. 106361, Apr. 2025, doi: 10.1016/j.conengprac.2025.106361.

[7] A. Surekha, K. R. Hemalatha, Y. Abhishek Reddy, A. Navya, G. Karthik Reddy, A. Janaki, "Automatic Liver Cancer Detection Using Deep Convolutional Neural Network," *International Journal of Emerging Research in Science, Engineering, and Management*, vol. 2, no. 1, pp. 45-53, January 2026, doi: 10.58482/ijersem.v2i1.7.

[8] Y. Cai *et al.*, "Non-invasive microwave detection system for rapid detection of intracerebral hemorrhage based on hydrogel metasurfaces and machine learning," *iScience*, vol. 28, no. 12, p. 113816, Oct. 2025, doi: 10.1016/j.isci.2025.113816.

[9] C.-T. Yen, J.-R. Wong, and C.-H. Chang, "Multi-Label Machine learning classification of cardiovascular diseases," *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, vol. 84, no. 1, pp. 347–363, Jan. 2025, doi: 10.32604/cmc.2025.063389.

[10] A. Abdalla *et al.*, "All-in-one machine learning framework for early detection and characterization of sugar beet diseases using hyperspectral imaging," *Smart Agricultural Technology*, vol. 12, p. 101633, Nov. 2025, doi: 10.1016/j.atech.2025.101633.

[11] D. Janani, Pothu Nikitha, Osuru Manohar, R Hemanth Kumar, Bommana Nagarjuna, Challa Hemanth Kumar, "Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification," *International Journal of Emerging Research in Science, Engineering, and Management*, vol. 2, no. 1, pp. 54-59, January 2026, doi: 10.58482/ijersem.v2i1.8.

[12] Y. Wang, Y. Wang, A. Wang, M. Humayun, and M. Bououdina, "Machine learning advances in food detection technologies," *Journal of Food Composition and Analysis*, vol. 148, p. 108596, Nov. 2025, doi: 10.1016/j.jfca.2025.108596.