

# Disease Diagnosis of Liver, Heart, and Brain Stroke Using ML and DL

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**Abstract**— Heart disease liver-related conditions, and brain stroke remain among the primary causes of global mortality, largely due to limitations in early and accurate diagnosis. Traditional clinical assessment methods depend heavily on manual analysis of patient records and medical images, which often results in diagnostic delays and increased health risks. To address these issues, this paper proposes an intelligent disease diagnosis framework that integrates Machine Learning (ML) and Deep Learning (DL) techniques. The system performs prediction of heart disease, liver disease, and brain stroke using a combination of structured clinical parameters and medical imaging data. Machine learning algorithms process numerical clinical features such as ECG readings and laboratory test results, while Convolutional Neural Networks (CNNs) analyze CT and MRI images for automated stroke identification. The proposed framework delivers accurate and efficient predictions, reduces manual diagnostic effort, and supports clinicians in timely decision-making. Experimental results demonstrate consistent and reliable predictive performance, confirming the effectiveness of the proposed approach for early disease detection and intelligent healthcare assistance.

**Index Terms**— Machine Learning, Deep Learning, Heart Disease Prediction, Liver Disease Diagnosis, Brain Stroke Detection, Convolutional Neural Network, Medical Decision Support, Healthcare Analytics.

## I. INTRODUCTION

In recent years, healthcare systems across the globe have faced growing challenges due to the rapid increase in chronic and life-threatening diseases. Conditions such as heart disease, liver disorders, and brain stroke account for a large proportion of global mortality and long-term health complications. Despite significant medical advancements, achieving early and accurate diagnosis remains difficult in many clinical environments.

Conventional diagnostic procedures rely heavily on manual examination of patient records, laboratory reports, and medical images supported by physician expertise. These processes are often time-consuming and susceptible to subjective variation, which may lead to delayed diagnosis, inconsistent clinical interpretation, and increased healthcare expenditure, particularly in resource constrained hospitals.

Heart disease is influenced by multiple risk factors including age, blood pressure, cholesterol levels, and lifestyle habits. Liver disorders frequently progress without noticeable early symptoms, resulting in detection at advanced stages.

Brain stroke represents a medical emergency where even minimal delays in diagnosis can cause irreversible neurological damage. These clinical challenges highlight the urgent need for automated and intelligent diagnostic support systems.

Recent developments in Artificial Intelligence (AI) have enabled effective data-driven solutions for healthcare analysis. Machine Learning (ML) methods are well suited for processing structured clinical data, while Deep Learning (DL) models especially Convolutional Neural Networks (CNNs) have achieved remarkable success in medical image interpretation, including CT and MRI scans.

Motivated by these advancements, this work presents an integrated diagnostic framework that combines ML and DL techniques for the prediction of heart disease, liver disease, and brain stroke. Structured clinical attributes are utilized for heart and liver analysis, whereas deep learning models perform automated stroke detection from imaging data. The proposed framework aims to deliver accurate, efficient, and reliable predictions, supporting early diagnosis and improving accessibility to intelligent healthcare services.

## II. RELATED WORK

Recent progress in Machine Learning (ML) and Deep Learning (DL) has greatly influenced the evolution of automated disease diagnosis and clinical decision-support technologies. Numerous studies have investigated the prediction of heart disease, liver disorders, and brain stroke by utilizing structured clinical datasets and medical imaging information [1][4]. These investigations highlight the growing importance of intelligent data-driven methodologies within modern healthcare systems.

In the context of heart disease prediction, several machine learning techniques including Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers have been extensively explored. These approaches primarily analyze patient attributes such as blood pressure, cholesterol levels, demographic information, and electrocardiogram (ECG) measurements to estimate cardiovascular risk [5], [6]. Although many models report favorable accuracy, their effectiveness is often limited by issues such as imbalanced datasets, inter-feature correlation, and reduced generalization across heterogeneous patient groups [7].

For liver disease diagnosis, existing research largely employs supervised learning models trained on biochemical and clinical indicators, including bilirubin values, liver enzyme readings, and protein concentrations. Prior studies [8], [9] have demonstrated satisfactory classification performance; however, prediction reliability may degrade due to noisy data, missing values, or inconsistent medical records. These limitations emphasize the importance of appropriate data cleaning, normalization, and feature optimization to enhance model robustness.

Significant advancements have also been reported in brain stroke detection through deep learning-based approaches, particularly Convolutional Neural Networks (CNNs). CNN models have shown strong capability in learning spatial and structural representations from CT and MRI images for identifying stroke-affected regions [10], [11]. Despite achieving high diagnostic accuracy, such models often require extensive annotated datasets and substantial computational resources, which can restrict their use in time-critical clinical scenarios [12]. To mitigate these challenges, hybrid ML-DL strategies have been

proposed to improve prediction reliability, though they may introduce additional model complexity and computational overhead [13].

Recent research trends increasingly focus on combining structured clinical parameters with imaging-based features to enhance diagnostic precision and interpretability [14]. These multimodal learning frameworks enable a more comprehensive assessment of disease conditions by capturing both physiological indicators and visual abnormalities present in medical images. Automated diagnostic systems further reduce reliance on manual interpretation, minimize human error, and facilitate faster clinical decision-making, ultimately contributing to improved patient outcomes. Inspired by these studies, the present work introduces an integrated ML-DL framework for heart disease, liver disease, and brain stroke prediction, providing a scalable and reliable solution for intelligent healthcare applications [15].

## III. DATASET OVERVIEW

The proposed work makes use of three independent datasets corresponding to heart disease, liver disease, and brain stroke analysis. Each dataset provides medically significant information essential for accurate disease evaluation. Structured tabular data are utilized for heart and liver prediction tasks, whereas brain stroke detection is performed using medical imaging datasets. Appropriate data organization and preprocessing procedures are implemented to ensure data reliability, enhance consistency, and facilitate efficient model training.

### A. Heart Disease Dataset

The heart disease dataset consists of essential clinical and physiological attributes commonly considered during cardiac assessment. These features correspond to well-known risk factors associated with cardiovascular disorders and are widely adopted in healthcare analytics research. Each attribute contributes meaningful information regarding a patient's heart condition, enabling learning models to capture relevant disease patterns

and perform accurate classification.

**TABLE I**  
PATIENT CLINICAL PARAMETERS FOR HEART DISEASE PREDICTION

Clinical Features	
Age	Maximum Heart Rate (MaxHR)
Gender	Exercise-Induced Angina
Chest Pain Category	ST Depression (Oldpeak)
Resting Blood Pressure	ST Segment Slope
Serum Cholesterol	Heart Disease Indicator
Fasting Blood Sugar	Resting ECG Result

*A. Liver Disease Dataset*

The liver disease dataset consists of clinically significant biochemical and physiological parameters, including bilirubin values, liver enzyme levels, albumin content, and hematological indicators. These features play an important role in evaluating hepatic function and detecting abnormal liver conditions. To ensure dataset reliability, missing entries are handled using mean-value imputation, and relevant attributes are selected for model training. The dataset represents complex and non-linear interactions among clinical variables, enabling accurate and stable liver disease prediction.

**TABLE II**  
SELECTED CLINICAL PARAMETERS FOR LIVER DISEASE ASSESSMENT

Clinical Attributes	
Patient Age	Total Serum Bilirubin (mg/dL)
Gender	Conjugated Bilirubin Level (mg/dL)
Duration Of Alcohol Intake (Years)	Indirect Bilirubin (mg/dL)
Average Daily Alcohol Consumption	Albumin Concentration (g/dL)
Hepatitis B Infection Status	Globulin Level (g/dL)
Hepatitis C Infection Status	Albumin-Globulin Ratio
Diabetes Condition	Alkaline Phosphatase (U/L)
Obesity Indicator	SGOT (AST) (U/L)
Platelet Count (lakhs/mm <sup>3</sup> )	Packed Cell Volume (PCV %)

*B. Brain Stroke Dataset*

The brain stroke dataset is composed of axial CT scan images classified into two categories: stroke- positive and normal cases. These images are utilized for training and validating deep learning models designed for automatic stroke identification. The dataset contains variations in image contrast, anatomical appearance, and acquisition settings, allowing the network to learn distinctive visual features related to stroke abnormalities.

Prior to model training, CT images are rescaled to

a uniform image size and intensity values are normalized to ensure consistent input representation and stable learning behavior.

Figure 1 shows a CT scan of a brain affected by stroke, in which abnormal tissue regions caused by reduced blood circulation are visible. These visual characteristics are essential for enabling deep learning models to recognize and learn patterns associated with stroke-related damage.

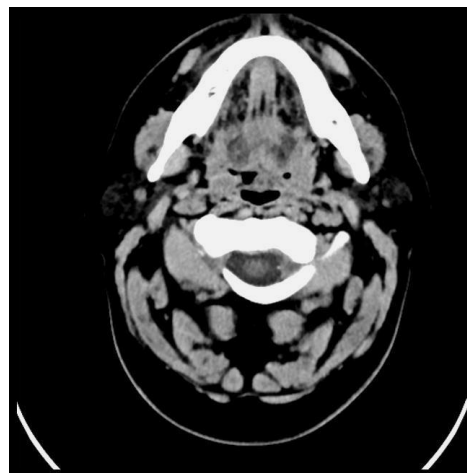


Fig. 1. CT scan demonstrating regions affected by brain stroke.

Figure 2 displays a CT image of a healthy brain with no noticeable abnormalities. Such samples represent normal anatomical structure and help the model effectively differentiate healthy cases from stroke-positive images.

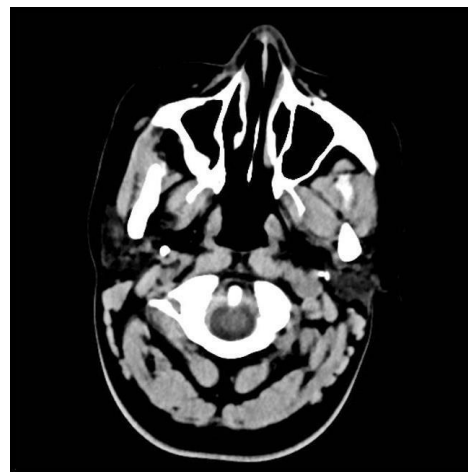


Fig. 2. CT scan of a normal brain without stroke symptoms.

The dataset is divided into distinct training and evaluation subsets to support objective performance assessment. The training portion is used to learn representative features, while the testing data validate the model's capability to perform accurately on previously unseen samples.

#### IV. METHODOLOGY

This study proposes an intelligent disease diagnosis framework that combines Machine Learning (ML) and Deep Learning (DL) techniques for the early identification of heart disease, liver disease, and brain stroke. The methodology is organized as a structured processing pipeline consisting of data collection, preprocessing, feature extraction, feature analysis, model construction, training, and outcome prediction. The overall system architecture is illustrated in Figure 3. The proposed framework is designed to efficiently manage both structured clinical records and unstructured medical imaging data. By integrating multiple prediction models within a unified environment, the system improves diagnostic consistency and supports clinicians in making accurate and reliable medical decisions.

##### A. System Architecture

The proposed system architecture processes both clinical records and medical imaging data to enable accurate disease prediction. Laboratory test results, ECG parameters, and CT or MRI brain images are provided as input to the system. Machine learning algorithms analyze structured clinical features for heart and liver diagnosis, supported by normalization and feature transformation techniques to improve learning efficiency. The architecture ensures smooth data flow and seamless integration of multiple prediction models, resulting in improved scalability, reliability, and overall diagnostic performance.

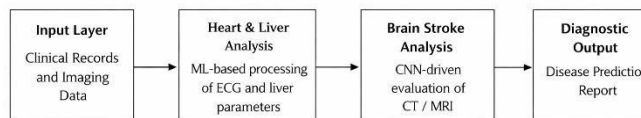


Fig. 3. Proposed architecture for integrated prediction of heart disease, liver disorder, and prediction of heart disease, liver disorder, and brain stroke.

##### B. Data Preprocessing

For the heart disease dataset, missing values are handled using mean-based imputation, and categorical attributes are encoded into numerical form to ensure compatibility with machine learning algorithms. Feature scaling is performed to normalize input ranges, which improves learning stability and accelerates model convergence.

In the liver disease dataset, biochemical and clinical parameters such as enzyme levels and blood indicators are cleaned and normalized to minimize noise and enhance prediction accuracy. Statistical imputation methods are applied to address incomplete records and preserve dataset consistency.

##### C. Feature Extraction and Selection

Important features are chosen by considering both medical significance and statistical contribution. For heart and liver disease prediction, parameters such as age, blood pressure, cholesterol values, enzyme measurements, and blood-related indicators are utilized. Careful feature selection improves classification performance while lowering computational overhead. It also eliminates irrelevant and duplicate variables, thereby enhancing the generalization capability of the models. In the case of brain stroke analysis, deep learning networks automatically extract discriminative spatial and texture-based features from medical images. These learned representations capture crucial visual characteristics such as intensity changes and structural irregularities. This automated feature learning approach removes the need for manual engineering and contributes to higher detection reliability.

##### D. Model Development

Distinct prediction models are designed according to the nature of each dataset. For heart disease analysis, ensemble based learning methods

integrating Random Forest, XGBoost, and Logistic Regression are applied to improve prediction stability and accuracy. Liver disease prediction is performed using a Random Forest classifier trained on selected clinical and biochemical features.

For brain stroke identification, deep learning architectures including ResNet and EfficientNet are implemented. These models are trained on preprocessed CT images to learn high-level visual representations that effectively differentiate stroke-affected areas from normal brain tissue.

Figure 4 demonstrates the processing flow used for heart disease assessment. Clinical parameters including ECG measurements, blood pressure, and cholesterol levels are evaluated

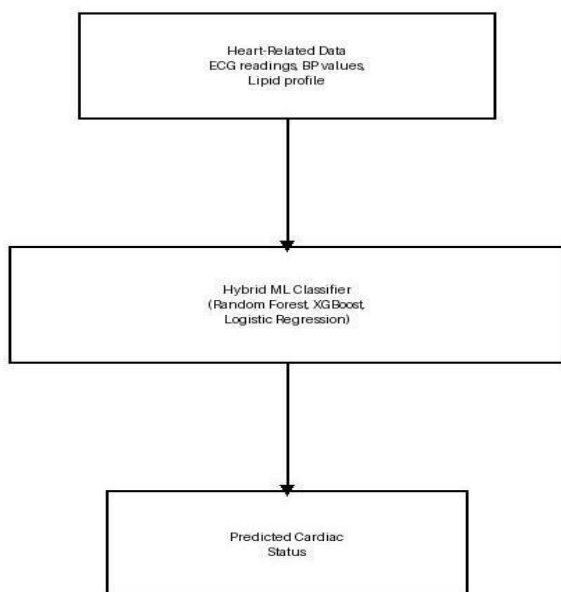


Fig. 4. Ensemble-based framework for heart disease classification.

through an ensemble of machine learning models. This combined learning approach enhances prediction consistency and accuracy by learning complementary data patterns. The final aggregated output enables dependable heart disease prediction and facilitates early clinical intervention.

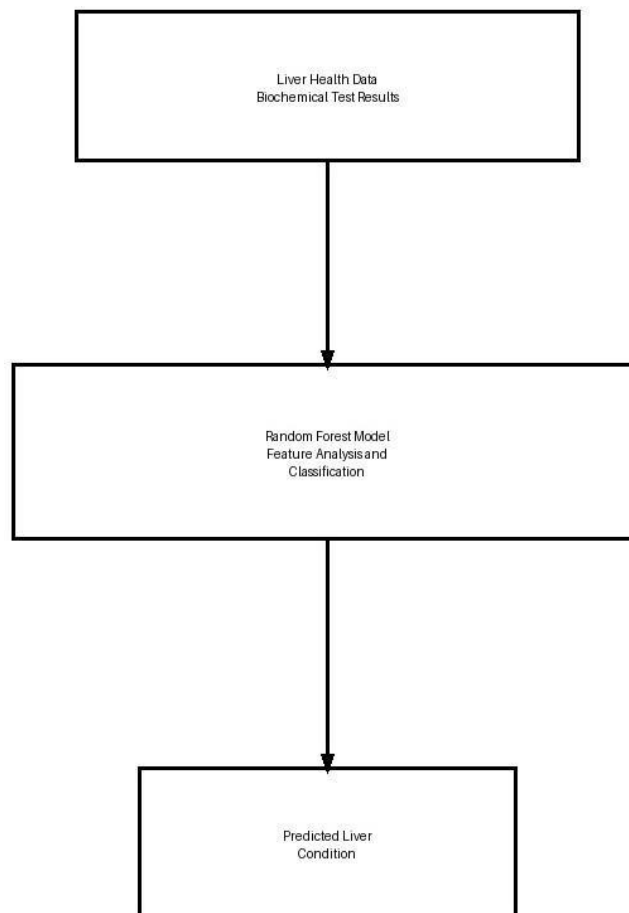


Fig. 5. Random Forest-based framework for liver disease prediction.

The workflow illustrated in Fig. 5 outlines the liver disease prediction procedure. Biochemical blood test features are examined using a Random Forest classifier, which is well suited for capturing complex and nonlinear relationships among clinical variables. The trained model produces a dependable prediction indicating whether liver abnormalities are present, thereby assisting in early medical assessment.

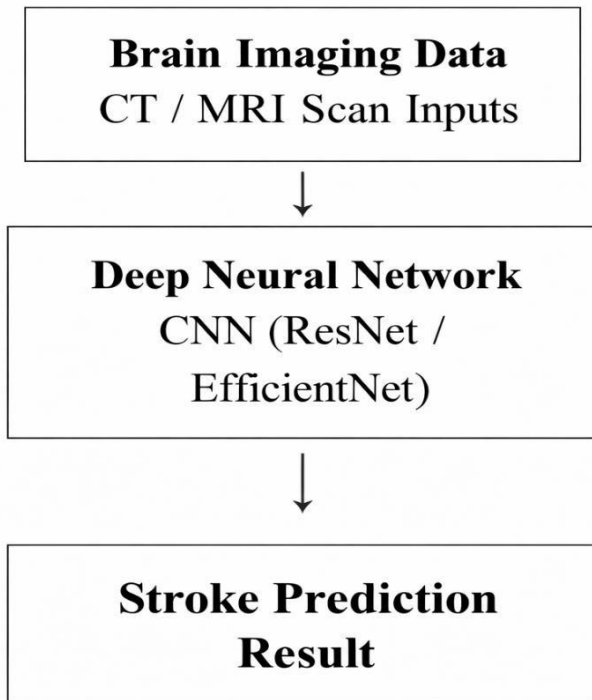


Fig. 6. Deep learning–based framework for brain stroke identification.

Figure 6 illustrates the workflow used for brain learning models across all disease prediction tasks. stroke detection. CT and MRI images are supplied to deep learning networks that extract meaningful spatial and structural features automatically. The trained model recognizes abnormal tissue characteristics associated with stroke and produces a final classification result, supporting rapid and accurate clinical diagnosis.

*E. Training and Validation*

The datasets are divided into independent training and testing groups to ensure objective model evaluation. During training, the algorithms learn representative patterns from the data, whereas the testing set is used to assess performance on unseen samples. Model evaluation is carried out using common classification measures such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). To improve generalization and minimize overfitting, cross-validation methods are applied, leading to stable and reliable predictive performance.

*F. Prediction and Output*

After training, the developed models are used to predict disease conditions for new patient inputs. Structured clinical data are evaluated through

machine learning algorithms, whereas medical images are analyzed using deep learning networks for stroke identification. The system generates accurate diagnostic results that support clinicians in prompt decision-making. Through the integration of multiple predictive modules, the framework achieves improved scalability, consistent performance, and enhanced diagnostic efficiency for practical healthcare deployment.

**V. PERFORMANCE EVALUATION AND RESULTS**

This section analyzes the experimental outcomes obtained from the proposed disease diagnosis framework designed for heart disease, liver disease, and brain stroke prediction. System performance is examined using widely adopted evaluation measures such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). The results highlight the predictive strength, consistency, and generalization ability of the combined machine learning and deep

*1. Heart Disease Performance Analysis*

The heart disease prediction module employs a multi-model learning framework where Random Forest, XGBoost, and Logistic Regression are jointly used for prediction on structured cardiovascular clinical attributes. This combined modeling approach captures diverse data characteristics and minimizes the bias and variance associated with individual classifiers.

As illustrated in Fig. 7, the ensemble approach achieves excellent classification performance across all evaluation metrics. The confusion matrix further indicates accurate identification of both healthy and affected cases, demonstrating the robustness and reliability of the proposed heart disease prediction framework.

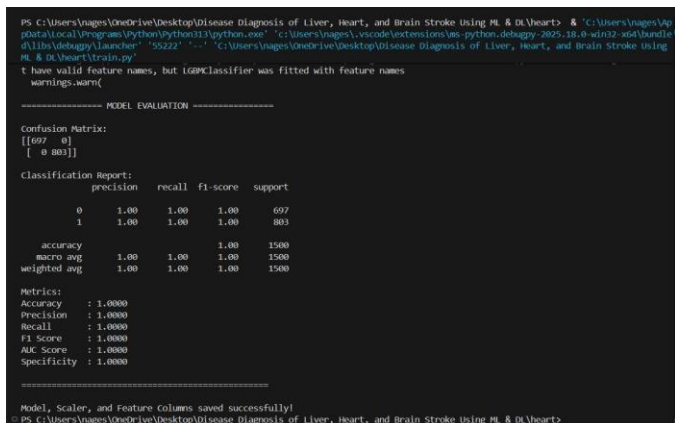


Fig. 7. Performance evaluation of the heart disease prediction model showing classification metrics and confusion matrix results.

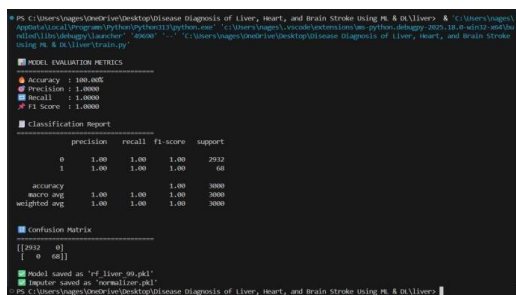
TABLE III  
HEART DISEASE PREDICTION PERFORMANCE

Performance Metric	Value
Accuracy	1.00
Precision	1.00
Recall	1.00
F1-Score	1.00
AUC Score	1.00

II. Liver Disease Performance Analysis

Liver disease classification is carried out using a Random Forest model trained on selected biochemical and clinical parameters, including bilirubin levels, enzyme measurements, and protein indicators. The model demonstrates strong learning capability and consistent predictive behavior.

The performance results shown in Fig. 8 reveal highly accurate classification outcomes. The absence of significant misclassification indicates the effectiveness of feature selection and preprocessing strategies employed in the proposed liver disease



diagnosis module.

Fig. 8. Performance evaluation of the liver disease prediction model including classification metrics and confusion matrix.

TABLE IV  
LIVER DISEASE PREDICTION PERFORMANCE

Performance Metric	Value
Accuracy	1.00
Precision	1.00
Recall	1.00
F1-Score	1.00

III. Brain Stroke Performance Analysis

For automated brain stroke detection, deep learning architectures based on ResNet50 and EfficientNet are utilized to analyze CT scan images. Images undergo preliminary processing involving size standardization, intensity adjustment, and contrast improvement, which supports effective feature learning and stable model convergence.

As presented in Fig. 9, the deep learning models achieve near-perfect accuracy and AUC values, reflecting strong discriminative capability. The networks successfully identify stroke-affected regions by learning spatial and structural patterns within brain images. Additionally, the stable performance across validation samples demonstrates the model's robustness and suitability for supporting timely clinical diagnosis.

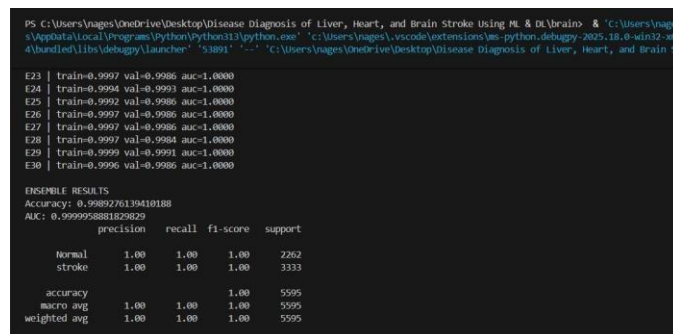


Fig. 9. Performance evaluation of the brain stroke prediction model showing accuracy, AUC, and classification metrics.

TABLE V  
BRAIN STROKE DETECTION PERFORMANCE

Performance Metric	Value
Accuracy	0.999
Precision	1.00
Recall	1.00
F1-Score	1.00
AUC Score	0.999

IV. Overall Performance Discussion

The experimental results indicate that the proposed multi- disease diagnostic framework achieves reliable and accurate performance across heart disease, liver disease, and brain stroke prediction tasks. The combination of ensemble based machine learning methods for structured clinical information with deep learning models for medical image processing contributes to strong predictive capability and improved generalization.

Consistent outcomes observed across multiple

evaluation measures confirm the applicability of the system in practical clinical decision-support settings. The obtained results demonstrate the framework’s ability to support early disease identification, minimize diagnostic burden, and enhance the overall efficiency of intelligent healthcare solutions.

In addition to performance accuracy, the framework highlights the importance of integrating diverse data sources for more comprehensive medical analysis. By effectively combining numerical clinical data with imaging features, the system captures both underlying patterns and visual indicators that are often missed in traditional approaches. This holistic analysis not only improves prediction reliability but also supports better clinical interpretation. Furthermore, the stability of results across different models suggests that the proposed approach can adapt well to real-world variations in medical datasets, making it a practical and scalable solution for modern healthcare environments.

TABLE VI  
COMPARATIVE PERFORMANCE ANALYSIS OF MACHINE LEARNING MODELS FOR HEART DISEASE RISK PREDICTION

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes (NB)	78.2	76.4	74.8	75.6
Support Vector Machine (SVM)	82.6	81.3	79.5	80.4
Multi-Layer Perceptron (MLP)	84.1	83.6	82.2	82.9
Random Forest (RF)	87.9	86.8	85.7	86.2
Voting Ensemble	89.6	88.9	87.4	88.1
<b>Proposed Hybrid Model (RF + XGBoost + LR)</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>

TABLE VII  
COMPARATIVE PERFORMANCE ANALYSIS OF MACHINE LEARNING MODELS FOR LIVER CIRRHOSIS PREDICTION

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	85.3	84.7	83.9	84.3
Support Vector Machine (SVM)	88.2	87.5	86.8	87.1
Random Forest	92.4	91.8	91.2	91.5
<b>Proposed Random Forest-Based Model</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>

**TABLE VIII**  
**COMPARATIVE PERFORMANCE ANALYSIS OF DEEP LEARNING MODELS FOR BRAIN STROKE PREDICTION USING MEDICAL IMAGE ANALYSIS**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN (Basic)	94.5	95.1	94.0	94.5	0.95
ResNet50	98.7	99.0	98.5	98.7	0.99
EfficientNetB0	99.1	99.3	99.0	99.1	0.99
<b>Proposed Ensemble (ResNet50 + EfficientNet)</b>	<b>99.9</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>0.999</b>

## VI. CONCLUSION

This research presented an intelligent disease diagnosis framework developed for the prediction of heart disease, liver disease, and brain stroke using Machine Learning (ML) and Deep Learning (DL) techniques. The proposed system integrates structured clinical parameters with medical imaging data to provide reliable and efficient diagnostic assistance. Ensemble learning models are applied for heart and liver disease analysis, while deep learning architectures are employed for automatic brain stroke identification, allowing the framework to analyze both numerical health indicators and spatial image features across heterogeneous datasets.

Extensive experimental analysis confirms that the proposed approach achieves stable and accurate performance across all three disease prediction tasks. High values obtained for evaluation metrics such as accuracy, precision, recall, and F1-score indicate the effectiveness of the developed models. The use of appropriate preprocessing techniques, meaningful feature selection, and optimized training strategies plays a significant role in improving prediction consistency and model generalization. Moreover, combining multiple learning models enhances diagnostic reliability and reduces the limitations associated with single-model approaches.

The results demonstrate that the proposed framework can serve as an effective clinical decision-support solution by enabling early disease detection and assisting medical professionals in timely assessment. By reducing dependence on manual diagnostic procedures and enabling fast automated analysis, the system contributes to improved diagnostic efficiency and patient care. Overall, the framework shows strong potential for practical

clinical deployment and provides a flexible foundation for the development of advanced intelligent healthcare systems in the future.

## VII. FUTURE SCOPE

While the proposed intelligent healthcare framework demonstrates encouraging performance, several opportunities exist for further enhancement. Expanding the study with larger and more diverse datasets collected from multiple hospitals and clinical centers can strengthen model robustness and improve generalization across different patient populations. Incorporating longitudinal medical records may also support better disease progression tracking and long-term risk assessment.

Future research can focus on integrating real-time physiological signals obtained from wearable devices and IoT-enabled medical sensors to enable continuous monitoring and early alert mechanisms. In addition, the adoption of explainable artificial intelligence (XAI) methods can improve transparency by helping clinicians understand and validate model predictions.

Further improvements may be achieved by exploring advanced deep learning techniques, including transformer-based architectures and hybrid CNN-RNN models, to handle complex medical imaging scenarios more effectively. Moreover, deploying the proposed framework on cloud and edge computing platforms can facilitate scalable, secure, and low-latency healthcare services suitable for real-world clinical environments.

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