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# Hybrid Machine Learning for Disease Diagnosis: A Review of Case Studies and Performance Evaluation Using Multi-Source Data

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**ABSTRACT**

The review paper discusses the development and assessment of hybrid machine learning frameworks for early disease diagnosis using multi-source clinical data. It highlights the importance of early disease forecasting in healthcare, as it allows for more efficient illness management, mitigating symptom severity, and decelerating disease development. Traditional disease prediction methods often face challenges, such as reliance on isolated data sources and the existence of imbalanced datasets. Hybrid machine learning models offer a robust approach to address these shortcomings by integrating the advantages of multiple machine learning methods to enhance predictive accuracy and resilience. Case studies have demonstrated the effectiveness of hybrid machine learning models in predicting coronary heart issues, Alzheimer's brain related issues, diabetes, and lung cancer. This review study discusses various studies on the use of deep learning models in medical image analysis, heart disease prediction, and brain tumor detection. The study discusses various methods, such as hybrid machine learning, ensemble machine learning, multi-source transfer learning, convolutional neural networks, and cloud-enabled access control models. It also discusses the role of advanced learning models such as AI and deep learning in early detection of chronic diseases and the spread infection-based diseases. The study also discusses the challenges and opportunities in using machine learning in cardiovascular disease prediction, with some focusing on the use of jellyfish optimization algorithm and others on the use of boosting techniques. The review concludes by focus attention on the importance of understanding the role of machine learning in healthcare and the potential for future advancements in this field.

**Keywords:** Machine Learning, Healthcare analysis, Deep Learning.

## INTRODUCTION

The capacity to forecast diseases early is essential for enhancing patient outcomes and minimising healthcare expenditures. Conventional approaches frequently depend on isolated data sources and may fail to encompass the intricate interactions of factors that lead to illness progression. Hybrid machine learning models, integrating several techniques and data sources, present a promising strategy to improve the reliability of early disease prediction with better accuracies. This document examines the creation and assessment of these models, emphasising the utilisation of multi-source clinical data.

### The Importance of Early Disease Prediction

Conventional Proactive illness forecasting is essential in contemporary healthcare. Identifying persons at elevated risk of disease facilitates prompt interventions, lifestyle alterations, and preventative therapies, thereby enhancing their quality of life [1]. Timely identification can facilitate more efficient illness management, mitigating symptom

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severity and decelerating disease development. Moreover, early prediction can substantially save healthcare expenses by averting hospitalisations and the necessity for costly interventions in advanced illness stages [3].

## Challenges in Traditional Disease Prediction

Conventional illness prediction methodologies frequently encounter numerous obstacles. These methods often depend on singular data sources, such as clinical evaluations or laboratory analyses, which may not offer a holistic perspective of a patient's health state [4]. Furthermore, conventional statistical models may find it challenging to accurately represent the intricate, non-linear associations between many risk factors and disease outcomes [5]. A notable difficulty is the existence of imbalanced datasets, wherein the quantity of patients with a certain disease is substantially lower than that of healthy persons, resulting in biassed predictions [6].

## The Role of Hybrid Machine Learning Models

Hybrid machine learning models provide a robust methods to address the weakness of traditional models. These algorithms integrate the advantages of various learning base methods to improve predictive accuracy with resilience [7]. Hybrid models can achieve in-depth understanding of an individual person's health by integrating data from many sources, including digital health records (EHRs), medical images, genomic patient data, and wearable sensors. Moreover, these models are capable of managing intricate, non-linear interactions and tackling the difficulties presented by imbalanced datasets using methods such as oversampling and cost-sensitive learning [9].

## Data Sources for Early Disease Prediction

### Electronic Health Records (EHRs)

Digital medical records (EHRs) constitute a comprehensive repository of clinical data, encompassing patient demographics, medical history, diagnoses, prescriptions, test findings, and clinical notes. Electronic Health Record data can be utilised to discern trends and risk factors linked to diverse diseases. Nonetheless, EHR data can be intricate and may necessitate comprehensive preparation to address absent values, discrepancies, and variances in data formats [11]. Natural Language Processing approaches can be utilised to extract pertinent information from non-structured clinical records, including symptoms, illness progression, and treatment outcomes [12].

### Medical Imaging

Medical 2D and 3D images-based modalities, including PET scans, MRI scan, CT scans, and X-rays based radiograph images offer critical understanding into the morpho-functional properties of the body. These images can facilitate the identification of early disease indicators, track disease advancement, and evaluate therapy efficacy. especially Convolutional Neural Networks (CNNs) in DL have demonstrated significant efficacy in analysing medical images and detecting nuanced patterns that may elude human observers [14].

### Genomic Information

Genomic data, which includes DNA sequencing and gene expression patterns, can help identify an individual's inherited predisposition to various diseases [15]. By analysis the genomic data, researchers can discern genetic markers linked to heightened illness risk and formulate personalised predictive models. Genomic data is frequently high-dimensional and necessitates specialised machine learning methodologies for processing [16]. Ethical problems of data privacy and genetic discrimination must be addressed when utilising genomic data for disease prediction [17].

### Wearable Sensors

Wearable sensors, including smartwatches and fitness trackers, may incessantly monitor diverse physiological data, such as heart rate, blood pressure, stress level, physical activities, sleep patterns, and body temperature. These data can yield significant information regarding a person's lifestyle and overall health condition. Machine learning algorithms can be developed to identify anomalies in wearable sensor data that may signify early indicators of sickness. Nonetheless, guaranteeing data quality, mitigating privacy issues, and amalgamating wearable sensor data with additional clinical data sources persist as substantial problems [19].

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## Approaches of Hybrid Machine Learning Models to Detect the Diseases

### Workflow in Machine Learning:

In case of disease prediction, we collect data based in desirable problem and diseases symptoms. As resources, we have medical electronic data (EHRs) and imaging data, including x-rays, MRIs, ultrasound images, and data from sensor-based devices, smartwatch, fitness trackers to monitor the fitness and collect the data from their physical activities and routine. Hybrid machine learning can handle text and imaging data including multi-source data to make prediction effectively. In the stage of diseases detection, we select the models and apply them with on unseen testing data after train the model, then validate the model after evaluating the model from collected data. After finalized model for diseases prediction, we deploy them on various platforms and devices.

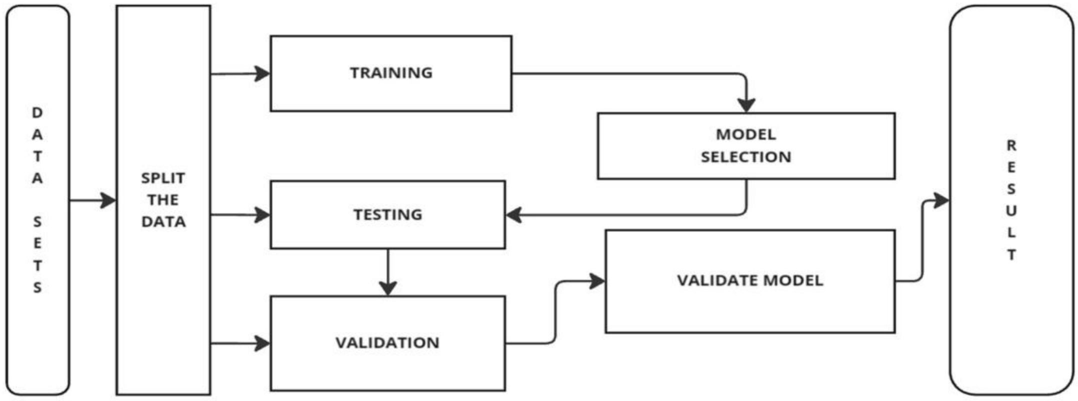


**Fig.1**: Data Flow in Hybrid Machine Learning

### Ensemble Techniques

Ensemble approaches integrate various machine learning models to enhance predictive accuracy and resilience. Prevalent ensemble methodologies encompass bagging, boosting, stacking, and voting. Random Forest, an ensemble approach based on bagging, is extensively utilised for illness prediction owing to its capacity to manage high-dimensional data and its robustness against overfitting [9]. Gradient Boosting, an ensemble strategy based on boosting, incrementally integrates weak learners to formulate a robust prediction model [6]. Stacking entails training a meta-learner to amalgamate the predictions of many base learners, whereas voting integrates the predictions of numerous models using a majority voting mechanism [21].

### Artificial Neuron Based ANN models

Especially deep learning based neural networks, exhibit significant potential in illness prediction owing to their capacity to learn intricate, non-linear correlations from extensive datasets [22]. Multi-Layer Perceptrons (MLPs) are feedforward neural networks utilised for classification and regression problems. Convolutional Neurons based Networks in the analysis of medical imaging data, whereas Recurrent Network (RNNs) are adroit in processed with sequential data, including time series data from wearable sensors [24]. Hybrid neural network topologies, which integrate many types of neural networks, can be constructed to capitalise on the advantages of each component [25].

### Hybrid Models Combining Traditional and Deep Learning Techniques

Hybrid models that integrate conventional machine learning methods with deep learning methodologies can enhance performance in disease prediction. A hybrid model may employ conventional feature selection methods to discern the most pertinent aspects from EHR data, then utilising a deep learning model to elucidate intricate correlations between these features and disease outcomes [11]. An alternative method involves use conventional

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machine learning methods to pre-process data or produce features, which are subsequently input into a deep learning model [2]. Hybrid methodologies can utilise the advantages of both conventional and deep learning techniques, resulting in more precise and resilient illness prediction models [26].

## Case Studies: Utilisation of Hybrid Machine Learning in Disease Prognostication

### Prediction of Heart Diseases (Coronary Heart Disease)

Coronary Heart Disease is a predominant cause of mortality globally, and early detection is essential for averting negative consequences [27]. Hybrid machine learning models have been created to forecast CHD risk by amalgamating medical data from many sources, including lifestyle factors, electronic health records, and genetic markers. For instance, K. Sk et al. employed a hybrid model that integrates Decision Tree (DT) and Ada Boosting algorithms to forecast coronary heart disease (CHD) [2]. Gregorius Airlangga et al. evaluated ensemble learning and neural networks for heart disease prediction, concluding that ensemble approaches such as Random Forest and Gradient Boosting consistently exhibited higher performance [9]. Rehan Ahmed and colleagues presented a hybrid approach utilising KNN and SVM classification methods for the prediction of heart illness [7]. These studies illustrate the capability of hybrid machine learning models to increase the precision and dependability of CHD prediction.

### Prediction of Alzheimer's Brain Cell Issues

Alzheimer's Brain Disease (AD) is a condition such as neurodegenerative that results in irreversible damage to neuronal cells, culminating in memory impairment and cognitive deterioration. Timely identification of Alzheimer's disease is essential for patient management and clinical investigation. Hybrid machine learning models have been created to forecast Alzheimer's disease risk by amalgamating data from various sources, including clinical information, MRI scans, and psychological evaluations. Sobhana Jahan et al. developed an explainable prediction model utilising multimodal data, comprising clinical data, MRI segmentation, and psychological evaluations, achieving good accuracy with Random Forest [23]. Rahmeh Ibrahim et al. enhanced the identification of Alzheimer's illness by deep learning combined with Particle Swarm Optimisation [13]. Yongping Chen et al. introduced a multi-features based fusion learning methodology for predicting Alzheimer's issue utilising resting state EEG signals [25]. These results underscore the capacity of hybrid machine learning models to improve the early-stage detection and help to provide right medical treatment of Alzheimer's disease.

### Prediction of Diabetes

Diabetes occurs when blood glucose levels increase and create a persistent metabolic condition. In the case of diabetes, persistent metabolic condition increase by glucose level in blood. Diabetes is a chronic metabolic disorder characterized by elevated blood sugar levels Timely identification of diabetes is crucial for mitigating complications and enhancing patient outcomes. Hybrid machine learning models have been created to forecast diabetes risk by amalgamating data from electronic health records, lifestyle variables, and genetic indicators. Shahid Mohammad Ganie et al. performed experiments utilising five boosting algorithms on the Pima dataset, attaining the highest accuracy rate with Gradient Boosting [30]. M. Jishnu Sai et al. suggested ensemble machine techniques for diabetes prediction, integrating Naive Bayes (Gaussian), k-NN, RF, Light GB, and Adaboost [31]. Karlo Abnoosian et al. introduced a novel multi-classification algorithms for diabetes prediction across more than one categories utilising an imbalanced Iraqi Patient Dataset using pipeline approaches [32]. These studies illustrate the efficiency of hybrid machine learning techniques in forecasting diabetes risk and enhancing detection at early stages.

### Prediction of Lung Carcinoma Cancer

Lung cancer is a primary contributor to cancer-related mortality globally. The prompt identification of lung cancer is essential for enhancing survival rates. Hybrid machine learning models have been created to forecast lung cancer risk by amalgamating data from medical imaging, clinical information, and environmental variables. Yossra H. Ali et al. utilised IoT and a multi-layer CNN model, enhanced through particle swarm optimisation, for lung cancer prediction [14]. These results underscore the capability of hybrid machine learning models to improve the compatibilities in detection and diagnosis of lung cancer on their early stages.

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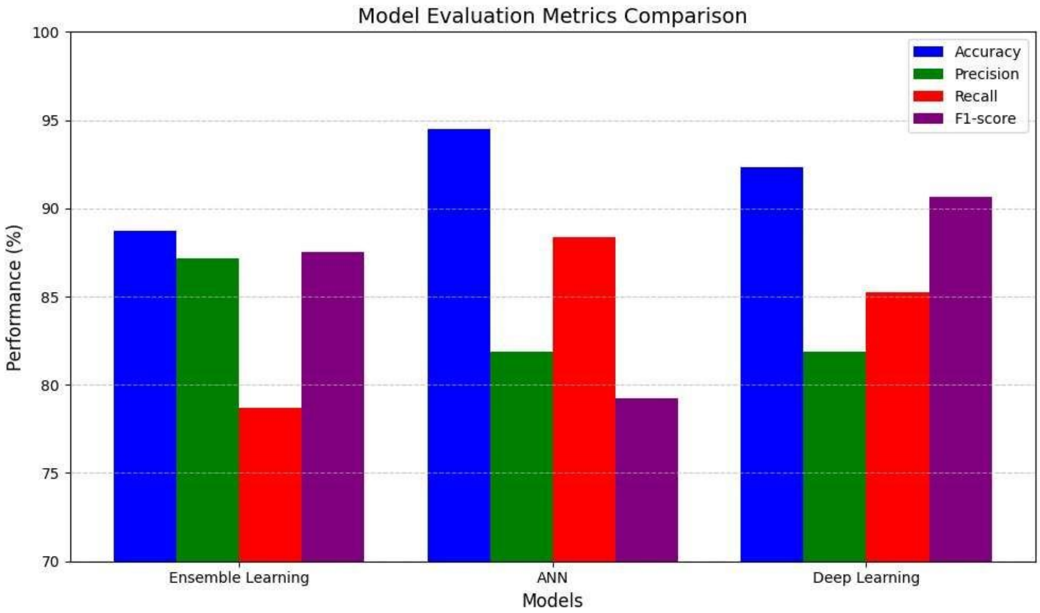
### Evaluation Metrics for Hybrid Machine Learning Models

The evaluation of a model, including traditional deep learning and machine learning even hybrid machine learning, improve the compatibilities of model on prediction. It helps us to identify model's performance using various evolution features, including accuracy, AUC-ROC Curve, precision, recall, confusion metric. Accuracy is not enough feature to discuss the suitability in prediction. Using more than one features, we can accurately identify the diseases on their stage earlier.




### Precision

Accuracy is a frequently employed evaluation statistic that assesses the overall factuality of all true values of model's predictions. It determines as the ratio of accurately classified occurrences to the total number of instances in predictions. Nevertheless, accuracy may be deceptive in the context of various non-balanced medical datasets, as a model can attain elevated accuracy by merely predicting the majority class [11].

### Accuracy

Precision quantifies the rational value of accurate positive predictions to the total positive predictions made by models. It is determined as the ratio of strongly positives to the total of true and false positive predictions [6]. Precision is especially critical when the expense of erroneous positive forecasts is substantial.

### Recall

Recall, or sensitivity, quantifies the rational value of true positive values from total values accurately recognised by the model. It is determined as the ratio of true positives to the total of false negatives and true positives. Recall is very important when the expense of incorrect negative predictions is significant.

### F1-Score

The F1-score is the harmonic mean value of recall values and precision values of that algorithms, offering a fair assessment of effectiveness of models. The calculation is expressed as F1-score value is equal to twice of division between multiplication of precision and multiplication of recall and sum of precision and recall values. In prediction, value of F1-score is advantageous when both precision and recall hold significance.

### The Evaluation AUC-ROC Curve

The AUC-ROC is a casually utilised metrics for assessing the efficacy of binary classification models [9]. It signifies the likelihood that a model will prioritise a randomly selected positive instance above a randomly selected negative

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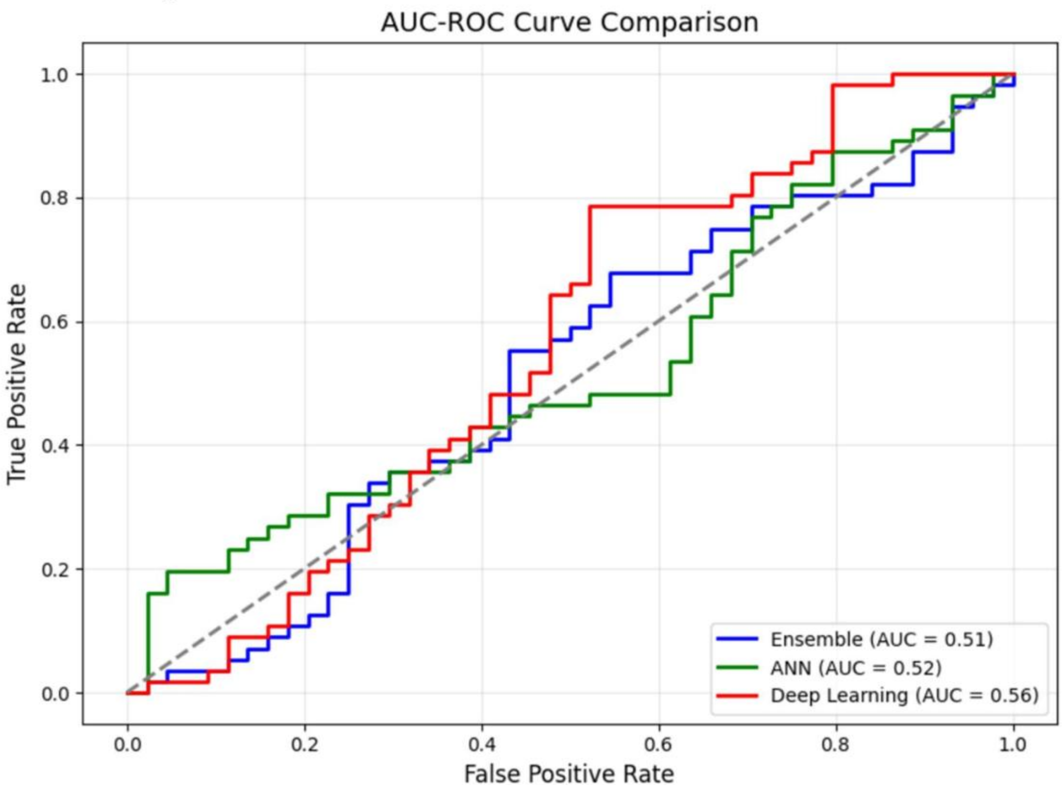
occurrence. The AUC-ROC curve of 0.5 signifies random performance, whereas an AUC-ROC of 1.0 denotes flawless performance.




## Challenges and Future Directions

### Data Quality and Availability

The accessibility and quality of medical data pose notable hurdles in the development and assessment of hybrid machine learning techniques for disease prediction on their early stages. Deficiencies in data, errors, and discrepancies in formats can profoundly affect model efficacy [17]. Guaranteeing data privacy and security is crucial, especially when handling sensitive health information [33]. Future research should prioritise the development of strong data preparation methodologies and the establishment of data sharing agreements that adhere to ethical and legal standards.

### Model Interpretability and Explainability

Model interpretability and explainability are crucial factors for establishing trust in hybrid machine learning models [23]. Healthcare practitioners must comprehend the methodology behind a model's predictions to make informed decisions. Methods such as feature importance analysis, SHAP values, and LIME help elucidate the predictions of intricate models [23]. Future research ought to concentrate on creating more interpretable models and delivering explicit explanations of model predictions to healthcare practitioners.

### Generalizability and Validation

Generalisability and validation are crucial for guaranteeing that hybrid machine learning models function effectively in practical healthcare environments. Models must be evaluated using independent datasets from varied populations to evaluate their capacity to generalise to new patients and environments [34]. External validation, in which a model is evaluated using data from diverse institutions or nations, is crucial for determining generalisability. Subsequent research must prioritise the execution of thorough validation studies and the formulation of methodologies for adapting models to diverse demographics and contexts.

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### Integration with Clinical Workflows

Incorporating hybrid machine learning models into current healthcare procedures presents a considerable hurdle. Models must be smoothly incorporated into EHR systems and other clinical tools to deliver timely and actionable insights to healthcare practitioners [35]. User interfaces must be crafted to be intuitive and user-friendly, while healthcare professionals require training to comprehend and utilise model predictions effectively. Subsequent research ought to concentrate on creating intuitive interfaces and incorporating models into clinical decision support systems to increase the chances of acceptance and efficacy of hybrid machine learning techniques in healthcare.

## CONCLUSION

Hybrid machine learning models present a viable method to improve the precision and dependability of early illness prediction utilising multi-source clinical data. By integrating the advantages of various algorithms and data sources, these models can surmount the constraints of conventional methods and yield significant insights for enhancing patient outcomes and minimising healthcare expenses. Despite considerable hurdles, continuous research and development initiatives are facilitating the extensive implementation of hybrid machine learning models in healthcare. The ongoing advancements in this domain possess the capacity to revolutionise sickness forecasting and alter healthcare provision.

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