

DEEP LEARNING MODELS FOR EARLY DISEASE DETECTION AND DIAGNOSIS

¹*P. Srinivas, ²G. Divya, ³V. Deepti Kiranmayi, ⁴Amitha Rose

¹*HOD in Computer Science, CH.S.D.ST. Theresa’s College for Women(A), Eluru.
^{2,3,4}Lecturer in Computer Science, CH.S.D.ST. Theresa’s College for Women(A), Eluru.



*Corresponding Author: P. Srinivas
HOD in Computer Science, CH.S.D.ST. Theresa’s College for Women(A), Eluru.
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ABSTRACT

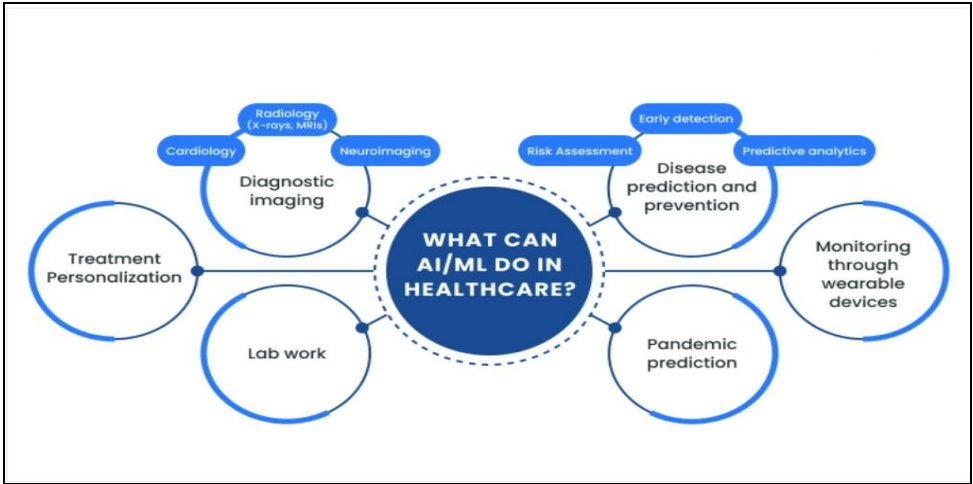
Early and accurate disease detection is critical for timely clinical intervention, improved patient outcomes, and optimized healthcare resource utilization. Recent advances in deep learning have revolutionized the field of medical diagnostics by enabling automated analysis of complex, multi-modal biomedical data such as medical images, genomics, and electronic health records. This paper presents a comprehensive review and empirical evaluation of state-of-the-art deep learning architectures including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformers, and hybrid models for early identification and staging of conditions such as cancer, Alzheimer's disease, and chronic kidney disease. Using large, diverse datasets, we highlight how specialized networks and hybrid frameworks can enhance feature extraction, improve classification accuracy, and identify subtle early-stage biomarkers, with some models achieving accuracies exceeding 95%. Practical implications, including improved precision and recall in real-world clinical scenarios, are discussed alongside challenges such as data heterogeneity, generalizability, and model interpretability. The study underscores the transformative potential of deep learning in early disease detection and advocates for continued efforts in developing robust, explainable AI systems to support clinical decision-making and personalized medicine.

KEYWORDS: Deep Learning, Convolutional Neural Networks (CNNs), Medical Imaging, Genomics, Electronic Health Records (EHRs), Explainable AI, Personalized Medicine.

1. INTRODUCTION

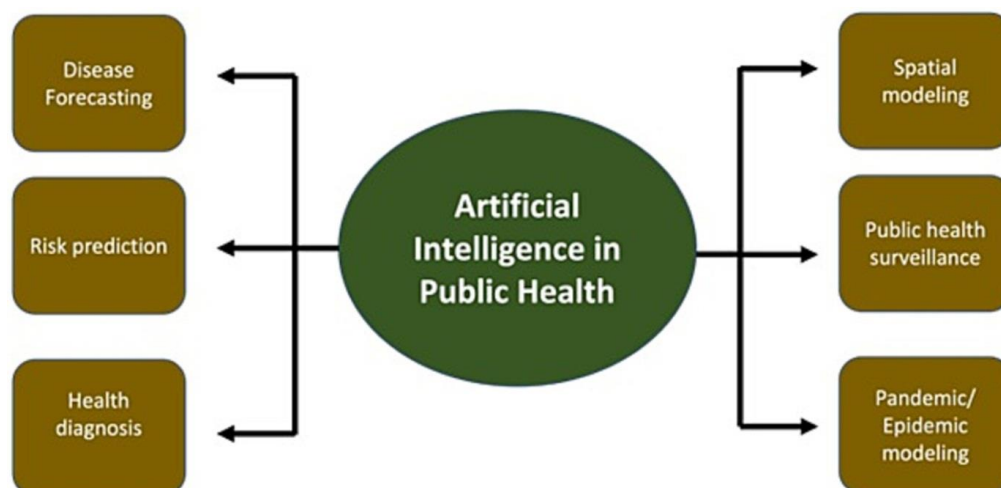
The integration of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare is rapidly transforming how medical diagnosis, treatment, and patient monitoring are conducted. AI and ML technologies play a pivotal role in enhancing the accuracy, efficiency, and personalization of healthcare

services through applications that span multiple domains. Diagnostic imaging, encompassing cardiology, radiology (including X-rays and MRIs), and neuroimaging, benefits significantly from AI’s ability to analyse complex medical images with precision, enabling more reliable detection and diagnosis of diseases.



Beyond imaging, AI-driven disease prediction and prevention strategies leverage advanced risk assessment models and predictive analytics to facilitate early detection, which is crucial to improve patient outcomes and reduce healthcare costs. The capacity to monitor patients remotely using wearable devices allows for

continuous, real-time health tracking, enabling earlier intervention and more personalized care plans. Additionally, AI applications extend to laboratory work, automating and accelerating test analyses to streamline workflows and increase diagnostic throughput.

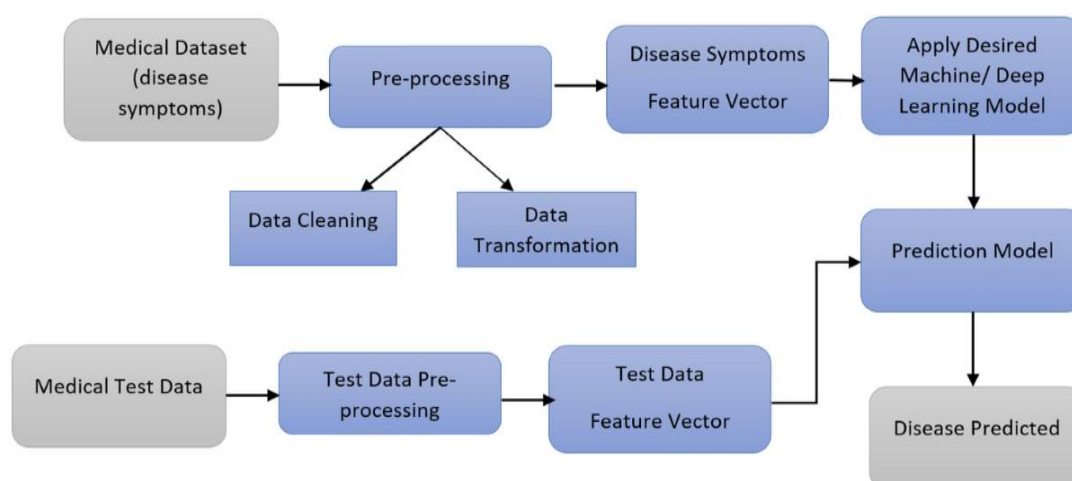


Pandemic prediction, a vital area underscored by recent global health events, illustrates how AI can analyse vast amounts of epidemiological data to forecast outbreaks and guide public health responses proactively. Finally, treatment personalization powered by AI platforms ensures that therapeutic decisions are tailored to individual patient profiles, optimizing efficacy and minimizing adverse effects.

Collectively, these AI-enabled innovations represent a paradigm shift in healthcare delivery, promising improved diagnostic accuracy, timely interventions, and enhanced patient experiences through data-driven insights and automation across clinical pathways.

1.1 AI and Machine Learning for Early Disease Detection and Diagnosis

Artificial Intelligence (AI) and Machine Learning (ML) are playing a transformative role in early disease detection, offering higher diagnostic accuracy, faster results, and more personalized care. By analysing large, complex datasets from various sources such as medical imaging, electronic health records, genetic information, and physiological signals AI systems can identify early signs of disease long before symptoms become clinically apparent.



Step-by-Step Process

1. Medical Dataset Collection

- Input: Raw dataset containing disease symptoms and patient information.

- Source: Hospitals, health records, or open medical datasets.

2. Pre-processing of Training Data

- **Data Cleaning:** Remove missing, inconsistent, or noisy data.
- **Data Transformation:** Normalize, encode categorical features, or scale numeric values.

3. Feature Vector Generation (Training)

- Extract key features (symptoms, biometrics, image patterns) from the cleaned dataset.
- Represent them as numerical feature vectors suitable for machine/deep learning.

4. Model Training

- Apply a **Machine Learning** or **Deep Learning** algorithm (e.g., Random Forest, CNN, RNN).
- Output: A trained **Prediction Model**.

5. Medical Test Data Input

- Collect new/unseen data for testing the model.

6. Pre-processing of Test Data

- Similar steps: Clean and transform test data for consistency.

7. Feature Vector Generation (Test)

- Extract and format test features to match the training format.

8. Prediction Phase

- Feed test feature vectors into the trained **Prediction Model**.

9. Disease Prediction

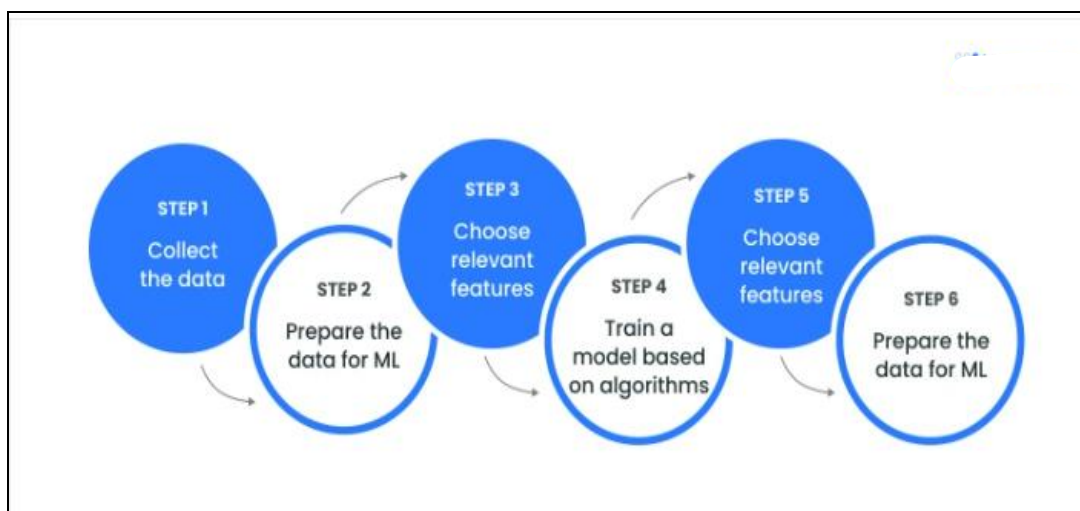
- Output: Disease class or diagnosis result is predicted.

1.2 Key Areas of Application

- **Cancer:** AI models analyse imaging data (e.g., mammograms, CT scans, MRIs) with high accuracy to detect early-stage breast, lung, skin, and prostate cancers. For example, Google's AI model for breast cancer reduced false positives by 5.7% and false

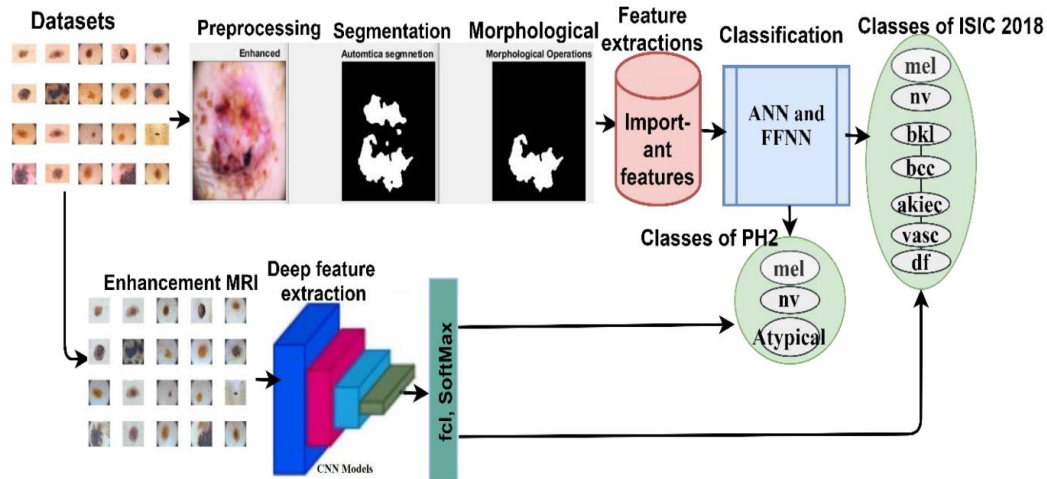
negatives by 9.4%. ML can also analyse bloodwork and genomic data to personalize treatment recommendations.

- **Cardiovascular Diseases:** ML assists in detecting arrhythmias from ECGs, identifying atherosclerotic plaques, and predicting stroke or heart failure risk using wearable device data. Some stroke risk models have achieved prediction accuracies of over 87%.
- **Neurological Disorders:** In diseases like Alzheimer's and Parkinson's, ML enables early diagnosis by analysing brain scans, voice recordings, and motor functions often before clinical symptoms are noticeable.
- **Diabetes:** Predictive models can forecast diabetes onset based on patient history, genetics, and lifestyle, while also identifying complications like diabetic retinopathy through retinal imaging.
- **Eye Diseases:** AI aids in the detection of glaucoma and age-related macular degeneration by analysing retinal scans, allowing for earlier treatment interventions.
- **Infectious Diseases:** AI is useful in tracking disease outbreaks, analysing viral genetic mutations, and predicting transmission patterns. It was notably used in early detection and response to COVID-19.
- **Liver and Respiratory Diseases:** Algorithms can detect early signs of liver fibrosis, fatty liver, COPD, and asthma using imaging data or respiratory audio patterns.
- **Bone and Joint Conditions:** AI enables early identification of arthritis and osteoporosis through X-rays and MRI scans.



Scenario

In the below image, two standard datasets, namely, ISIC 2018(International Skin Imaging Collaboration) and PH2, were used for diagnosing dermatological diseases.



1.3 Steps in AI-Based Skin Disease Detection

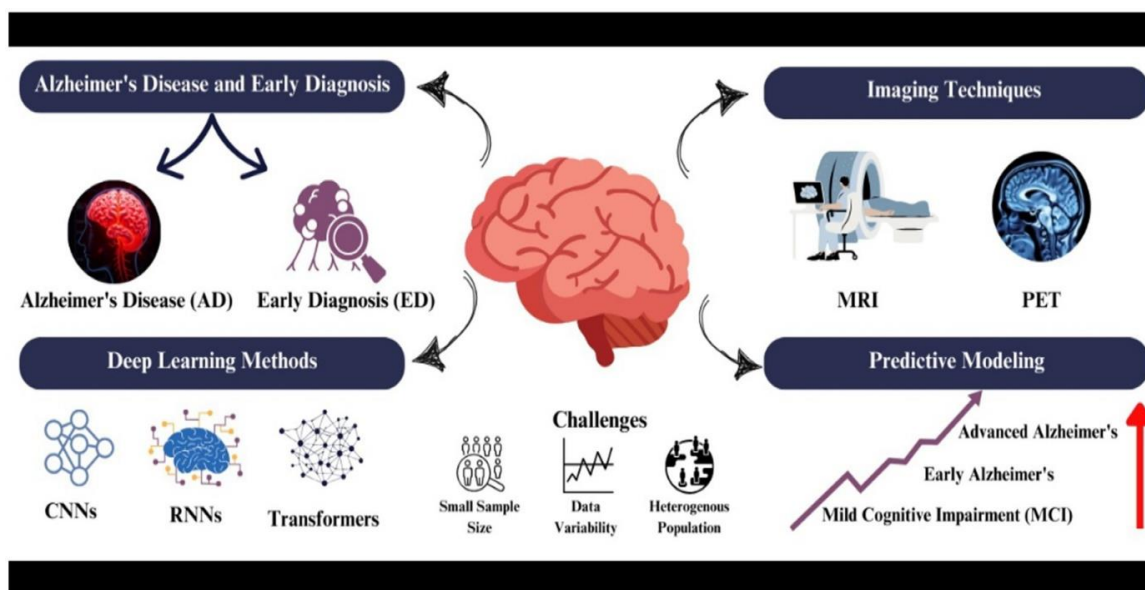
Step	Description
1.Dataset Collection	Collect dermoscopic images from datasets like ISIC 2018 and PH2 .
2. Preprocessing	Enhance image quality (e.g., contrast, noise reduction) to improve analysis.
3. Segmentation	Automatically segment the lesion area from the skin using segmentation models.
4. Morphological Ops	Apply morphological operations (e.g., dilation, erosion) to refine the region.
5. Feature Extraction	Extract important features (shape, texture, color) manually or statistically.
6. Classification	Use ANN (Artificial Neural Network) or FFNN (Feed-Forward Neural Network) to classify the features.
7. Classes (PH2)	Classify into mel , nv , or atypical (PH2 dataset labels).
8. Classes (ISIC 2018)	Classify into mel , nv , bkl , bcc , akiec , vasc , df .
9.Alternate Path: CNN	Use CNN-based deep feature extraction directly on enhanced images.
10.Softmax Layer	Final classification using fully connected layer + softmax .

ISIC 2018 Classes

- **mel**: Melanoma
- **nv**: Melanocytic nevus
- **bkl**: Benign keratosis
- **bcc**: Basal cell carcinoma
- **akiec**: Actinic keratosis

- **vasc**: Vascular lesions
- **df**: Dermatofibroma

Advancements in deep learning for early diagnosis of Alzheimer's disease using multimodal neuroimaging.

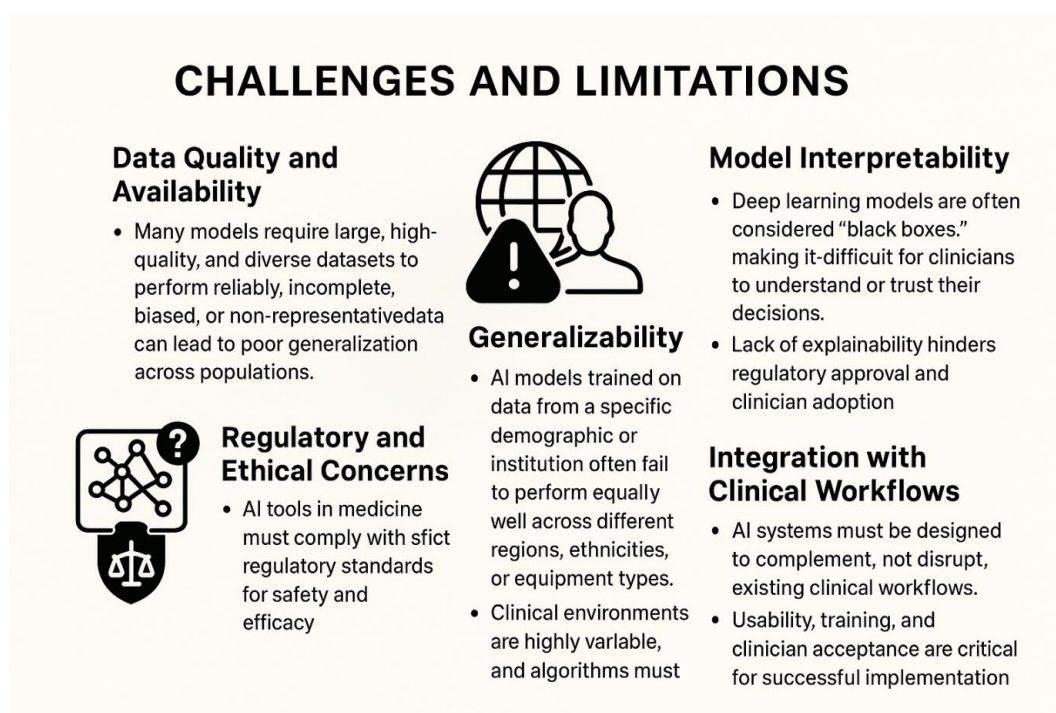


1.4 Real-Time AI-Based Disease Detection Systems

Disease	AI Tool/ Platform	How It Works	Technology Used
Skin Cancer	SkinVision	Analyses photos of skin lesions from smartphone to assess cancer risk.	Deep CNNs
COVID-19	AI Chest X-ray Analysis	Detects COVID-19 pneumonia from X-rays or CT scans.	ResNet, DenseNet
Breast Cancer	Google LYNA	Analyses pathology slides to detect breast cancer metastases.	Deep learning on histology
Brain Tumor	AI MRI Segmentation Tools	Segments tumor regions in brain MRI for diagnosis and surgical planning.	U-Net, SegNet, DeepLab

2. CHALLENGES AND LIMITATIONS

Despite significant advancements, integrating AI and machine learning into clinical practice faces several important challenges.



1. Data Quality and Availability

Many models require large, high-quality, and diverse datasets to perform reliably. Incomplete, biased, or non-representative data can lead to poor generalization across populations.

Access to labeled medical data is limited due to privacy regulations and ethical concerns.

2. Generalizability

AI models trained on data from a specific demographic or institution often fail to perform equally well across different regions, ethnicities, or equipment types.

Clinical environments are highly variable, and algorithms must be robust enough to handle real-world noise and variability.

3. Model Interpretability

Deep learning models are often considered "black boxes," making it difficult for clinicians to understand or trust their decisions.

Lack of explainability hinders regulatory approval and clinician adoption.

4. Regulatory and Ethical Concerns

AI tools in medicine must comply with strict regulatory standards for safety and efficacy.

There are ethical concerns around patient consent, algorithmic bias, and the use of patient data.

5. Integration with Clinical Workflows

AI systems must be designed to complement, not disrupt, existing clinical workflows.

Usability, training, and clinician acceptance are critical for successful implementation.

3. CONCLUSION

Deep learning has emerged as a powerful tool for early disease detection and diagnosis, offering high accuracy, speed, and scalability in analysing complex medical data such as images, signals, and electronic health records. Advanced architectures like CNNs, RNNs, and Transformers have demonstrated exceptional performance in identifying early-stage symptoms of diseases like cancer, Alzheimer's, and cardiovascular conditions.

Despite challenges such as data quality, interpretability, and clinical integration, deep learning continues to evolve with innovations like explainable AI and multi-modal learning. These advancements promise to enhance early diagnosis, enable personalized treatment, and ultimately improve patient outcomes. As research and real-world applications advance, deep learning is poised to become an essential component of future healthcare systems.

BIBLIOGRAPHY

1. <https://ijsrm.net/index.php/ijsrm/article/view/6223>
2. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5196927
3. <https://www.sciencedirect.com/science/article/pii/S1877050925014796>
4. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12069014/>
5. <https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2025.1557177/full>
6. <https://www.jneonatalurg.com/index.php/jns/article/view/3655>
7. <https://www.nature.com/articles/s41598-025-05568-y>
8. <https://link.springer.com/article/10.1007/s10462-025-11258-y>
9. <https://binariks.com/blog/ai-machine-learning-for-early-disease-detection/>
10. <https://www.mdpi.com/2079-9292/10/24/3158>
11. https://www.frontiersin.org/files/Articles/1557177/fninf-19-1557177-HTML/image_m/fninf-19-1557177-gr0001.jpg
12. <https://www.frontiersin.org/journals/public-health/articles/10.3389/fpubh.2023.1196397/full>
13. <https://biomedpharmajournal.org/vol16no3/hybrid-model-deep-learning-method-for-early-detection-of-alzheimers-disease-from-mri-images/>
14. <https://www.sciencedirect.com/science/article/pii/S1877050925014796>