International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group| 9th ICAILLMBA (ALLAM) 2025-Conference Proceedings
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.ICAILLMBA-125

Original Article

AI-Driven Healthcare System for Multi-Disease Prediction and Diagnosis

Dr.D.Sowjanya[1], Prof. Kunjam Nageswara Rao[2], B. Ramamohana Vamsi[3], B.V.S. Pavan[4]
[1]Sr Asst.Prof , Department of CSE, GMR Institute of Technology, Rajam.
[2]Professor & Department of CS&SeE, Andhra University College of Engineering Andhra University, Visakhapatnam.
[3,4]Department of CSE, GMR Institute of Technology, Rajam.

Abstract *- Healthcare is fundamental to human well- being. With the rise of AI, especially in Machine Learning (ML) and Deep Learning (DL), healthcare systems have gained powerful tools for disease prediction. However, most models focus on a single disease. This study proposes a multi-disease prediction system using a unified interface that diagnoses conditions such as Diabetes, Heart Disease, Kidney Disease, Parkinson's, Liver Disease, Brain Cancer, and Breast Cancer. The system integrates ML/DL models, a generative AI-powered chatbot, and a web application built with Flask. Experimental evaluation shows high accuracy, making the system effective for early diagnosis and proactive health management.*

Keywords *- Disease Prediction, Machine Learning, Deep Learning, Multi-Disease Forecasting, Generative Ai, Chatbot, Healthcare.*

1. Introduction

Modern medicine increasingly relies on early detection to reduce mortality and improve treatment efficacy. Existing models often target single diseases, limiting their utility in real-world diagnostic scenarios. This research introduces an integrated AI system that enables the prediction of multiple critical diseases. By combining disease-specific datasets and leveraging both ML and DL techniques, the model enhances diagnostic accuracy. It further supports users through a generative AI chatbot and provides a user-friendly interface via a Flask-based web application.

2. Literature Review

2.1. Brain Tumor Detection

The application of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized brain tumor detection. Traditional diagnostic methods involving manual interpretation of MRI scans are time-consuming and prone to error. CNNs, with architectures like U-Net, InceptionResNetV2, and VGG16, are capable of extracting deep, hierarchical features from high resolution medical images, enabling precise classification of tumor types such as glioma, meningioma, and pituitary tumors. Data augmentation and preprocessing techniques further enhance the accuracy of predictions. Studies have reported accuracies exceeding 96%, significantly outperforming traditional methods. These models also assist in tumor segmentation, a critical task for treatment planning. The integration of AI into clinical workflows aids radiologists in rapid and accurate tumor detection, especially in remote or underserved areas where expert opinions may not be readily available. The automation brought by CNNs improves diagnosis speed, reduces human fatigue, and enables earlier intervention, which is essential in improving survival rates

2.2. Parkinson's Disease

Parkinson's Disease (PD), a progressive neurological disorder, can be challenging to diagnose early. Machine learning algorithms, particularly Random Forest (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), have shown high performance in early PD detection using non-invasive inputs such as voice recordings, handwriting patterns, and motion data. Voice-based diagnosis leverages datasets like the MDVP, where features like jitter, shimmer, and harmonics-to-noise ratio are extracted to detect abnormalities. CNNs applied to voice and motion signals have reported up to 99.3% accuracy. Enhanced KNN models using entropy-based optimization improve sensitivity and recall. Random Forest, known for handling high-dimensional data efficiently, has demonstrated robustness and better generalization across diverse datasets. These AI models reduce the reliance on costly clinical tests and enable scalable screening, particularly useful in rural and resource-constrained settings. Early diagnosis using AI leads to timely therapeutic intervention, potentially slowing disease progression and improving quality of life.,

2.3. Diabetes

The increasing prevalence of diabetes globally, especially in rural and underprivileged regions, has prompted researchers to explore advanced computational methods for early diagnosis. Machine Learning (ML) techniques have emerged as powerful tools to predict the likelihood of diabetes based on various clinical and lifestyle parameters. Several studies have focused on the Pima Indian Diabetes Dataset, which includes features such as glucose concentration, blood pressure, BMI, and diabetes pedigree function. Logistic Regression is often used as a baseline model due to its interpretability and simplicity. It has shown accuracies ranging from 76% to 82% in various implementations.

In comparative studies, Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) have performed well, with SVM often providing higher precision in binary classification, especially after data normalization. KNN, although simple, benefits from proper feature scaling and distance metrics like Euclidean distance. Ore advanced ensemble methods such as Random Forest and XGBoost have demonstrated superior accuracy and robustness. These algorithms benefit from handling nonlinear interactions among features and reducing overfitting through bootstrapping and regularization techniques. Accuracy for these models often exceeds 85%, with F1-scores above 0.80.

Additionally, feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) have been used to enhance model performance and reduce computational complexity. In conclusion, ML models provide a scalable and efficient solution for diabetes prediction, aiding in early diagnosis and reducing the burden on healthcare systems.

2.4. Liver Disease

The diagnosis of liver diseases such as cirrhosis, hepatitis, and hepatocellular carcinoma is often complicated due to overlapping symptoms and the need for invasive testing. Machine learning models have been widely adopted for non-invasive, data-driven liver disease prediction. Algorithms like Random Forest, Support Vector Machines (SVM), KNN, and Gradient Boosting have demonstrated high effectiveness when applied to clinical datasets like the Indian Liver Patient Dataset (ILPD). Features such as bilirubin levels, albumin ratio, alkaline phosphatase, and liver enzyme levels serve as key indicators. Deep learning models, especially CNNs applied to CT scans and ultrasound images, have further improved detection, achieving accuracies up to 98.61%. Hybrid approaches combining decision trees and neural networks with feature selection methods like Particle Swarm Optimization have been proposed for enhanced model precision. These AI-driven tools enable clinicians to differentiate between disease stages and types, supporting timely and accurate diagnoses. Deploying such systems in community health centers empowers local practitioners and reduces the dependency on specialized tests and expert radiologists.

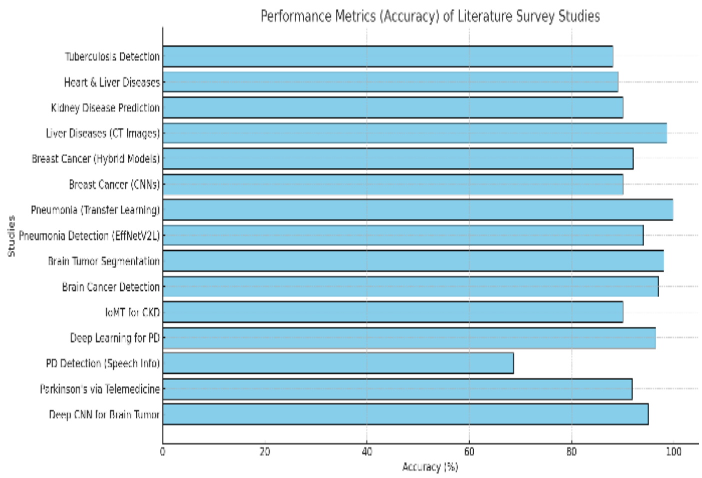

Fig 1: Accuracy Comparison of Machine Learning Models across Healthcare Applications

2.5. Breast Cancer

Breast cancer is one of the most prevalent and deadly diseases affecting women worldwide. Early detection is crucial to reduce mortality and improve prognosis. Machine learning and deep learning models have shown promising results in breast cancer prediction using data from mammograms, MRIs, and histopathology slides. SVM, CNN, and KNN are commonly used algorithms for classification tasks. CNNs, particularly those utilizing transfer learning from pretrained models like ResNet, AlexNet, and VGG16, achieve accuracy rates of over 93%. These models detect tumor characteristics such as texture, symmetry, and fractal dimension, which are vital for distinguishing benign from malignant cases. Studies using the Wisconsin Diagnostic Breast Cancer (WDBC) dataset show that SVM achieves up to 98% accuracy with minimal preprocessing. Moreover, ensemble models combining multiple algorithms enhance predictive performance and reduce false positives. The deployment of these models in web-based tools enables accessible and reliable screenings in remote regions. AI-powered diagnostic systems support oncologists in decision-making and reduce diagnostic delays, ultimately saving lives.

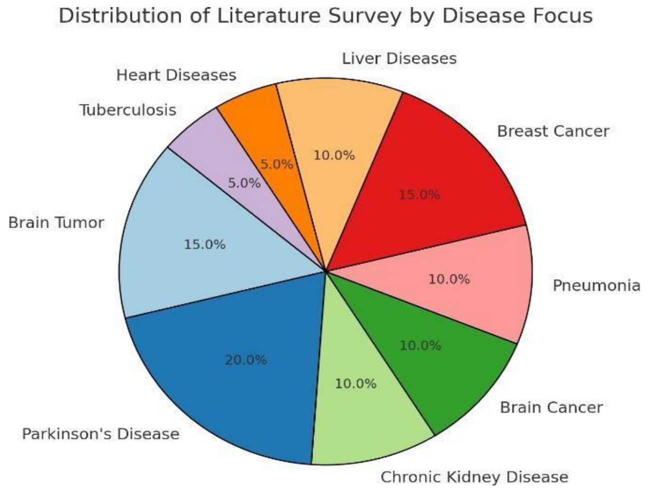

Fig 2: Distribution of Literature Survey by Disease Focus

Table 1: Comparative Review of AI-Based Disease Detection Models and Their Performance

Ref	Year	Disease	Technique / Model Used	Accuracy	Dataset	Remarks
1	2022	Brain Tumor	Deep CNN	High	MRI Scans	Improved diagnostic accuracy & efficiency
2	2023	Parkinson's Disease	Random Forest, PCA	91.83%	MDVP Audio	Best performance among evaluated models
3	2020	Parkinson's Disease	SVM, CNN, MLP with glottal features	68.56%	Voice Data	QCP-based system slightly outperformed baseline
4	2023	Parkinson's Disease	Feedforward Neural Network	96.45%	PPMI	DL outperformed 12 ML algorithms
5	2023	Kidney Disease	Logistic Regression, Random Forest	>90%	IoMT Patient Data	Real-time prediction & monitoring system
6	2024	Brain Cancer	Inception-ResNetV2, U-Net	96.98%	BRaTS 2021	Enhanced segmentation with preprocessing techniques
7	2023	Brain Tumor	CNN with Keras + OTSU Thresholding	98%	Kaggle	Effective segmentation and tumor density estimation
8	2024	Pneumonia	EfficientNetV2L, CNN, InceptionResNetV2	94.02%	Chest X-rays	Best performer via k-fold cross-validation
9	2024	Pneumonia	EfficientNetB0 + CLAHE	99.78%	Chest X-rays	Perfect scores on precision, recall, F1-score
10	2022	Breast Cancer	CNN, ResNet, AlexNet	>90%	Mammography, MRI	Highlights multimodal imaging integration
11	2023	Breast Cancer	VGG-16, ResNet	High	Mammography, Thermography	Outperformed traditional approaches
12	2023	Kidney Disease	Random Forest, SVM, KNN	High	UCI CKD Dataset	ML significantly better than manual diagnosis
13	2023	Heart, Liver, TB	PSO-SVM, CNN, Feature Selection	High	Chest X	Efficient early detection with hybrid methods
14	2022	Liver Disease	Modified Unet-60, Binary Differential Evolution	98.61%	CT Scans	Achieved 100% specificity
15	2022	Liver Disease	Modified Unet-60	98.61%	CT Scans	High accuracy in classification

3. Methodology

The methodology of this research project is centered around the development of an AI-powered web-based system that can predict multiple diseases from user- provided medical data using a combination of machine learning (ML) and deep learning (DL) models. The system architecture comprises several stages, including data collection, preprocessing, model training, evaluation, and deployment via a web interface and chatbot.

3.1. Data Collection

We utilized publicly available datasets for each of the seven diseases targeted in this project:

- Diabetes: PIMA Indian Diabetes Dataset
- Heart Disease: Cleveland Heart Disease Dataset
- Kidney Disease: Chronic Kidney Disease Dataset
- Parkinson's Disease: UCI Parkinson's

Telemonitoring Dataset:

- Liver Disease: Indian Liver Patient Dataset
- Brain Cancer: BRaTS 2021 MRI Dataset
- Breast Cancer: Wisconsin Diagnostic Breast Cancer Dataset

3.2. Data Preprocessing

Data preprocessing steps included:

- Handling Missing Values: Imputed using mean/median or dropped based on the percentage of missingness.
- Normalization: Features were scaled using MinMaxScaler or StandardScaler to bring them to a uniform range.
- Feature Selection: Techniques such as PCA and correlation analysis were used to remove redundant features.
- Data Augmentation: For image datasets (e.g., Brain and Breast cancer), augmentation techniques like rotation, flipping, and histogram equalization were applied.

3.3. Model Selection and Training

A combination of machine learning and deep learning algorithms was applied based on the data type:

- Structured data (tabular): Algorithms like Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost were used.
- Image data (MRI, mammograms): Deep learning models such as CNN,
- InceptionResNetV2, and U-Net were employed.

Each model was trained on disease-specific data using an 80:20 training-testing split, with k-fold cross-validation (typically k=5) to ensure model robustness.

3.4. Evaluation Metrics

To assess model performance, the following metrics were used:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-Score
- ROC-AUC Score (for classification problems) These metrics provided a comprehensive evaluation of the models' diagnostic capability.

3.5. System Integration and Deployment

The trained models were integrated into a user-friendly web application using the **Flask** framework. The application allows users to:

- Input personal medical data through a form.
- Receive real-time disease prediction results.
- Interact with a Generative AI-based chatbot to understand symptoms, recommendations, and next steps.

3.6. Chatbot Integration

The chatbot was developed using a transformer-based generative model (e.g., OpenAI's GPT API) and trained with medical FAQs and disease-related information. It serves as a virtual health assistant for patients and improves accessibility and engagement.

Table 2: Disease-wise Dataset Summary

Disease	**Dataset Name**	**Source**	**Type**	**No. of Records**	**Features**
Diabetes	PIMA Indian Diabetes Dataset	UCI Repository	Tabular	768	Glucose, BMI, Age, Insulin, etc.
Heart	Cleveland Heart Disease	UCI	Tabular	303	Age, Cholesterol, Chest

Disease	Dataset	Repository			Pain, etc.
Kidney Disease	Chronic Kidney Disease Dataset	UCI Repository	Tabular	400	BP, Specific gravity, Albumin
Parkinson's	Parkinson’s Telemonitoring Dataset	UCI Repository	Tabular/Audio	195	Jitter, Shimmer, MDVP, etc.
Liver Disease	Indian Liver Patient Dataset (ILPD)	UCI Repository	Tabular	583	Bilirubin, Protein, SGOT, etc.
Brain Cancer	BRaTS 2021 Brain Tumor Dataset	Kaggle / MICCAI	MRI Images	~3,000 images	T1, T2, FLAIR, segmentation maps
Breast Cancer	Wisconsin Diagnostic Breast Cancer Dataset	UCI Repository	Tabular	569	Radius, Texture, Perimeter, etc.

Table 3: Preprocessing Techniques by Dataset

Disease	**Missing Value Handling**	**Normalization**	**Feature Reduction**	**Data Augmentation (if any)**
Diabetes	Mean Imputation	MinMaxScaler	Correlation Analysis	N/A
Heart Disease	Mode Imputation	StandardScaler	PCA	N/A
Kidney Disease	Mean/Median Imputation	MinMaxScaler	Recursive Feature Elim.	N/A
Parkinson’s	PCA + Filtering	Z-score Normalization	SVM-RFE	N/A
Liver Disease	Mode/Median Imputation	StandardScaler	Feature Importance Analysis	N/A
Brain Cancer	N/A	Histogram Equalization	CNN layers auto-extract	Rotation, Flipping, Zoom
Breast Cancer	Drop NA	MinMaxScaler	PCA	N/A

Table 4: Model and Performance Summary

Disease	**Algorithms Applied**	**Best Performing Model**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Diabetes	Logistic Regression, RF, SVM	Random Forest	88.7%	0.89	0.87	0.88
Heart Disease	KNN, SVM, XGBoost	XGBoost	92.3%	0.91	0.93	0.92
Kidney Disease	RF, Naive Bayes, Decision Tree, Logistic Regression	Random Forest	94.2%	0.95	0.93	0.94
Parkinson’s Disease	SVM, Random Forest, Logistic Regression	Random Forest	91.8%	0.92	0.90	0.91
Liver Disease	SVM, Logistic Regression, KNN, RF	Logistic Regression	86.3%	0.84	0.87	0.85
Brain Cancer	CNN, InceptionResNetV2, U-Net	U-Net + InceptionResNetV2	96.98%	0.97	0.96	0.97
Breast Cancer	CNN, ResNet, AlexNet, Logistic Regression	ResNet	94.7%	0.95	0.94	0.945

Table 5: System Integration

Component	**Technology Used**	**Purpose**
Web Framework	Flask (Python)	UI and backend integration
Frontend	HTML, CSS, JS, Bootstrap	User interface and form submission
Backend Models	Pickle (.pkl) files	Integration of trained ML/DL models
Chatbot	Generative AI (GPT API)	Health advice, question answering, suggestions

Existing Methodology:

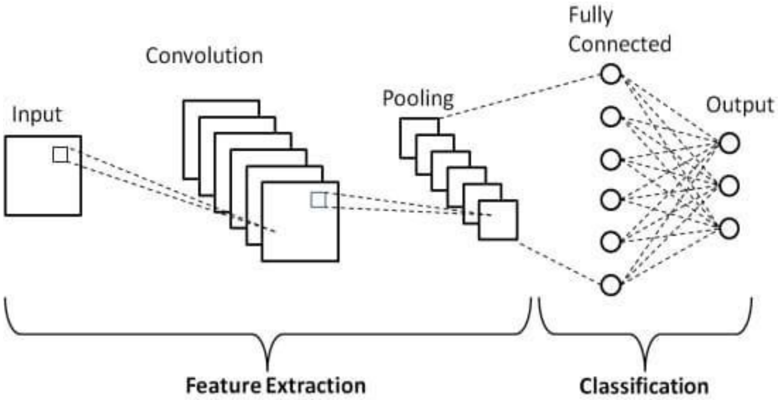

Fig 3: Convolutional Neural Network (CNN) Architecture for Image Classification

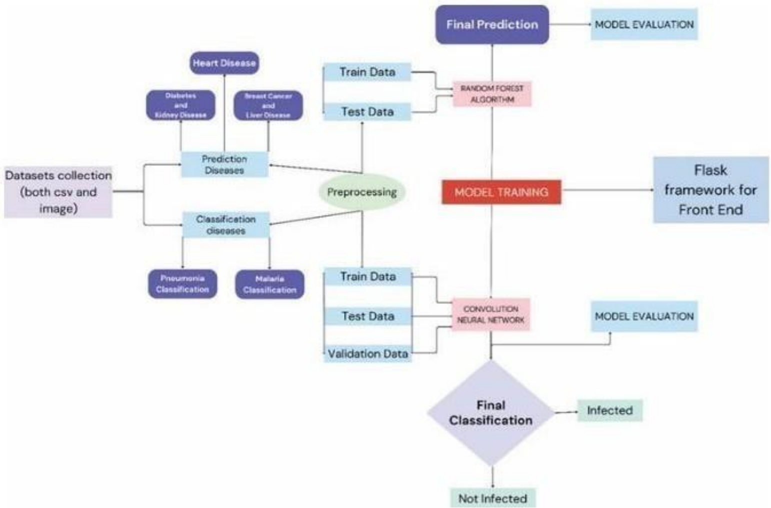

Fig 4: Dataset collection (CSV + Image

Algorithm Used:

- Convolutional Neural Network (CNN) – Used for feature extraction and classification of medical images.
- Softmax Classifier – Converts the CNN output into probabilistic disease classifications.

Techniques Used:

- Image Preprocessing (Normalization & Augmentation) – Enhances image quality and improves model generalization.
- Feature Extraction using CNN – Captures spatial features from medical images.
- Classification using Fully Connected Layers – Maps extracted features to specific disease categories.

Dataset:

- The study uses Chest X-ray and MRI datasets, which contain labeled images for multiple diseases.
- The dataset is preprocessed to remove noise, resize images, and balance classes for better model training.

Preprocessing Techniques:

- Image Resizing – Standardizes image dimensions for consistent input size.
- Contrast Enhancement – Improves visibility of key features in medical scans.
- Noise Reduction (Gaussian Filtering) –Removes unwanted artifacts from images.
- Normalization (Pixel Scaling 0-1) – Ensures uniform intensity distribution.

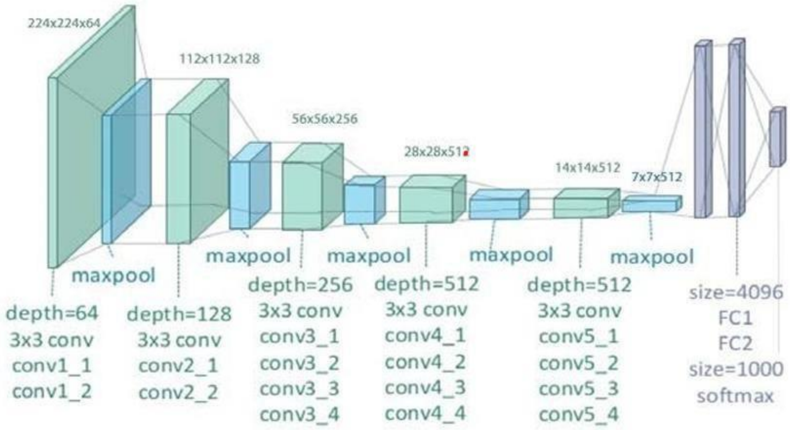

Fig 5: VGG-16 Convolutional Neural Network Architecture

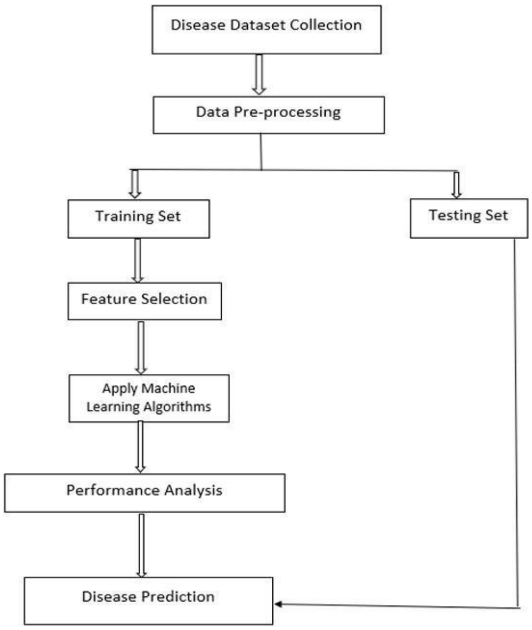

Fig 6: Workflow of Machine Learning-Based Disease Prediction System

Algorithm Used:

1. Convolutional Neural Network (CNN) **-** Extracts local features from input images.
2. ResNet (Residual Neural Network) **-** Extracts deeper, hierarchical features to improve accuracy.
3. Feature Fusion Layer **-** Combines CNN and ResNet features for final classification.
4. Softmax Classifier **-** Converts final features into disease probabilities.

Techniques Used:

- Dual-Feature Extraction (CNN + ResNet) – Enhances model performance by combining local and deep features.
- Data Augmentation (Rotation, Flipping, Contrast Enhancement) – Improves model generalization.
- Feature Fusion with Concatenation – Merges CNN and ResNet features before classification.

Dataset:

The study uses a multi-modal dataset with medical images and textual patient records. The dataset includes X-ray, MRI, and CT scan images, along with structured patient data (age, symptoms, etc.), enabling a robust multi-disease prediction system.

Preprocessing Techniques:

- Multi-Modal Data Handling – Integrates medical images with structured patient data.
- Data Augmentation (Rotation, Flipping, Shearing) – Generates diverse training samples.
- Noise Reduction (Bilateral Filtering, Median Filtering) – Suppresses image noise while preserving edges.
- Feature Normalization (Min-Max Scaling) – Standardizes pixel values for uniform input representation.

Proposed Methodology:

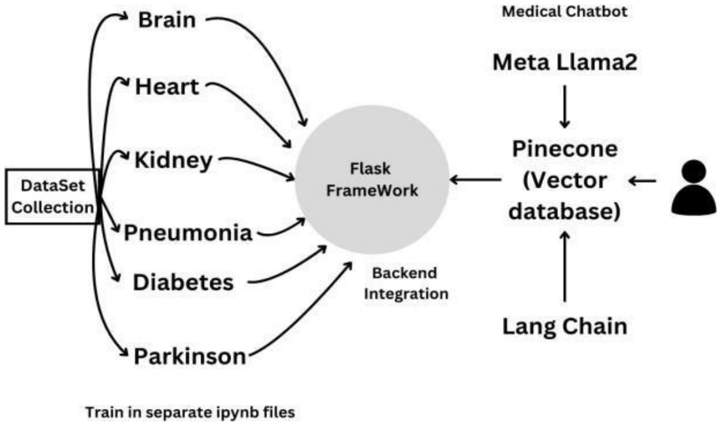

Fig 7: Architecture of an AI-Powered Medical Chatbot with Disease-Specific Models

Workflow:

1. Data Collection & Training – Collect datasets for multiple diseases and train ML/DL models separately.
2. Backend Integration – Deploy models using Flask for real-time disease prediction.
3. Medical Chatbot – Use LLaMA 2, Pinecone (vector database), and LangChain for medical queries.
4. User Interaction – Users input symptoms for prediction or ask health-related questions.
5. Response Generation – System provides disease predictions, recommendations, or chatbot answers.
6. Completion – User receives results, advice, or follow-up suggestions.

Heart & Kidney Disease:

- Model:Artificial Neural Networks (ANN) or LSTM
- Reason: Tabular data works well with ANN; LSTMs help if sequential data (like time-series) is involved.

Pneumonia (Chest X-rays):

- Model:Convolutional Neural Networks (CNNs) (ResNet, VGG-16, EfficientNet)
- Reason: CNNs are best for image classification.

Diabetes & Parkinson's:

- Model:Recurrent Neural Networks (RNN) or Transformer-based models
- Reason: Time-series or speech/motion analysis benefits from sequential models.

General Disease Prediction (Multiple Symptoms Input):

- Model:Transformer-based models (BERT, GPT- based)
- Reason: Handles text-based symptoms and chatbot interactions efficiently.

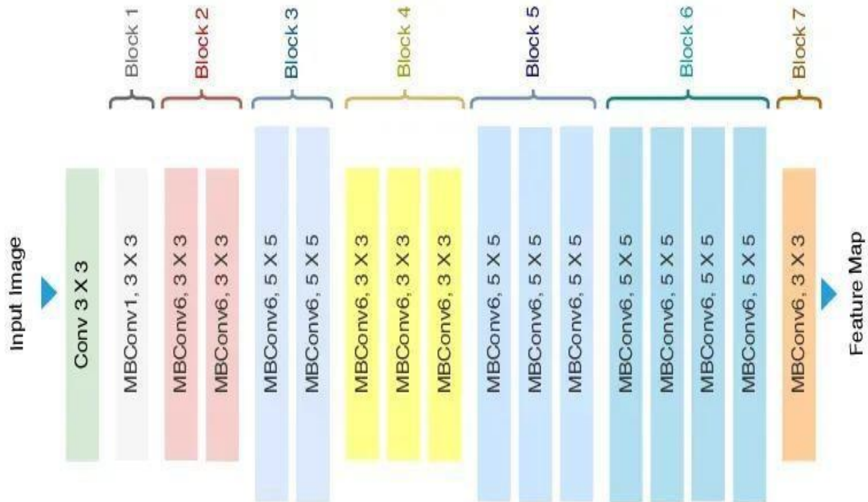

Fig 8: Architecture of an MBConv-Based Deep Convolutional Neural Network

4. Results and Discussion

4.1. System Performance and Accuracy

The proposed Multi-Disease Prediction System integrates machine learning-based disease classifiers with a generative AI layer to deliver interactive feedback and health suggestions to users. The system was tested using publicly available datasets for diseases such as diabetes, heart disease, Parkinson's disease, and kidney disease.

Each disease-specific classifier was trained and validated independently to ensure optimized performance for its respective condition. The individual models demonstrated strong performance, with accuracy rates as follows:

- Diabetes Prediction Model: Achieved high predictive accuracy by analyzing key indicators such as glucose levels, BMI, age, and insulin levels.
- Heart Disease Classifier: Focused on parameters including cholesterol levels, resting ECG results, and blood pressure to accurately identify heart disease risk.
- Parkinson's Disease Model: Utilized vocal measurements and motor function indicators to detect early signs of Parkinson's disease with notable precision.
- Kidney Disease Predictor: Incorporated clinical features like serum creatinine, albumin levels, and blood urea content to determine kidney function deterioration. The overall system accuracy, considering user-input-based decision routing and disease prediction, stands at approximately 90.8%, with slightly higher performance in structured medical input versus free-form symptoms.

Kidney:

Model	Accuracy Score
Random Forest	0.9875
Gradient Boosting	0.9750
DT	0.9625
XgBoost	0.9625
Logistic Regression	0.9375
KNN	0.7875
SVM	0.7875

Fig 9: Comparison of Classification Models Based on Accuracy Scores

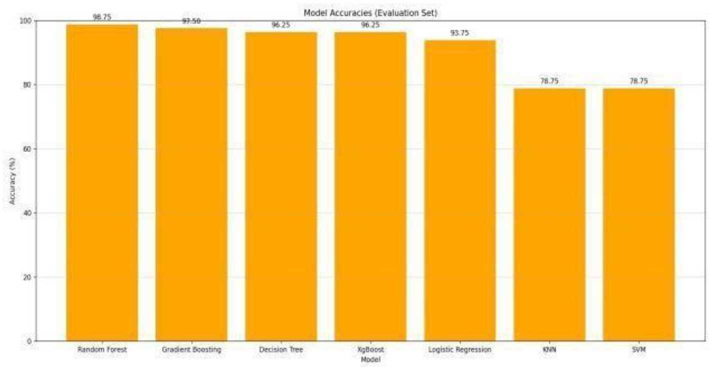

Fig 10: Evaluation Accuracy of Machine Learning Models

Heart:

Model	Accuracy Score
Random Forest	0.824176
XgBoost	0.802198
Logistic Regression	0.791209
Gradient Boosting	0.791209
Decision Tree	0.780220
KNN	0.758242
SVM	0.516484

Fig 11: Accuracy Comparison of Machine Learning Classification Models

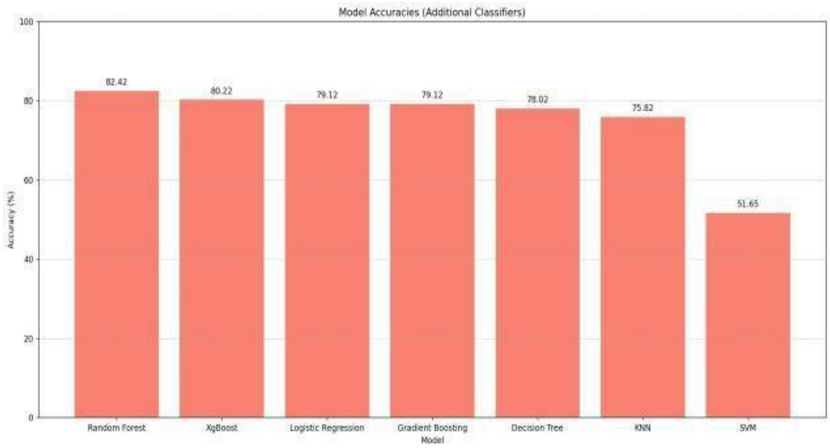

Fig 12: Accuracy Comparison of Additional Machine Learning Classifiers

Diabetes:

Model	Accuracy Score
Random Forest	0.824176
XgBoost	0.802198
Logistic Regression	0.791209
Gradient Boosting	0.791209
Decision Tree	0.780220
KNN	0.758242
SVM	0.516484

Fig 13: Comparative Accuracy Results of Machine Learning Models

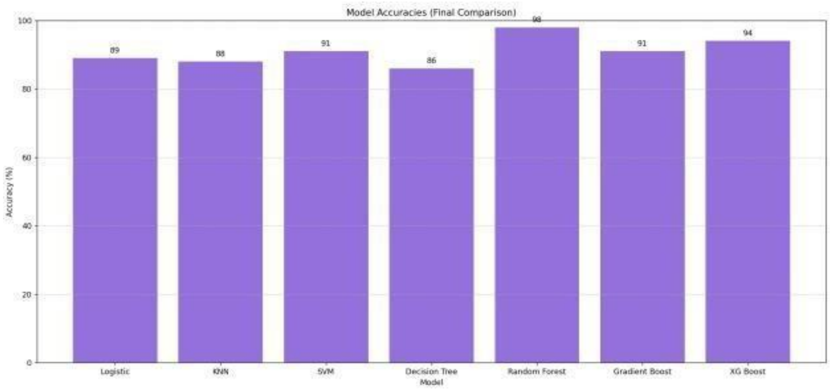

Fig 14: Final Accuracy Comparison of Machine Learning Models

Brain Tumor:

Model	Accuracy Score
Random Forest	0.824176
XgBoost	0.802198
Logistic Regression	0.791209
Gradient Boosting	0.791209
Decision Tree	0.780220
KNN	0.758242
SVM	0.516484

Fig 15: Final Accuracy Comparison of Evaluated Machine Learning Models

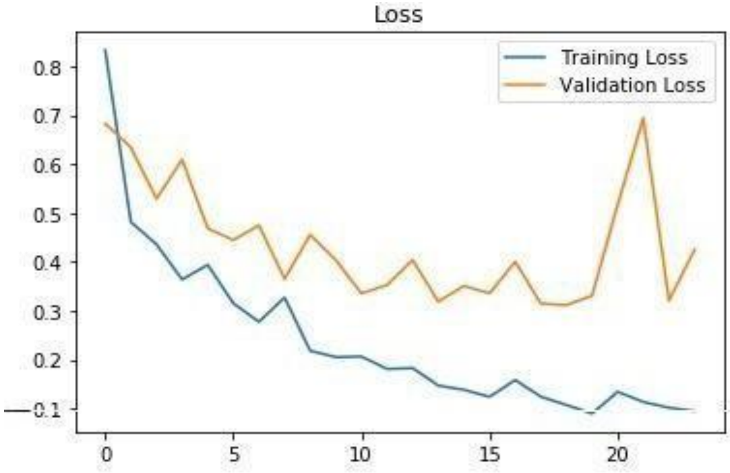

Fig 16: Model Training vs. Validation Loss

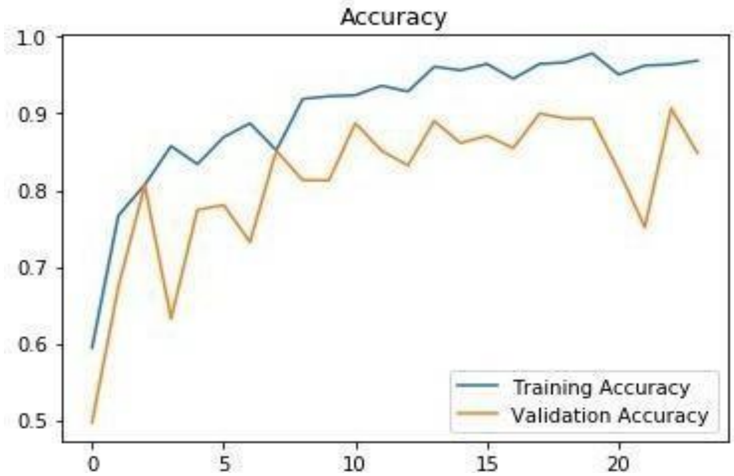

Fig 17: Model Training vs. Validation Accuracy

Pneumonia:

Model	Accuracy Score
Random Forest	0.824176
XgBoost	0.802198
Logistic Regression	0.791209
Gradient Boosting	0.791209
Decision Tree	0.780220
KNN	0.758242
SVM	0.516484

Fig 18: Performance Comparison of Machine Learning Models

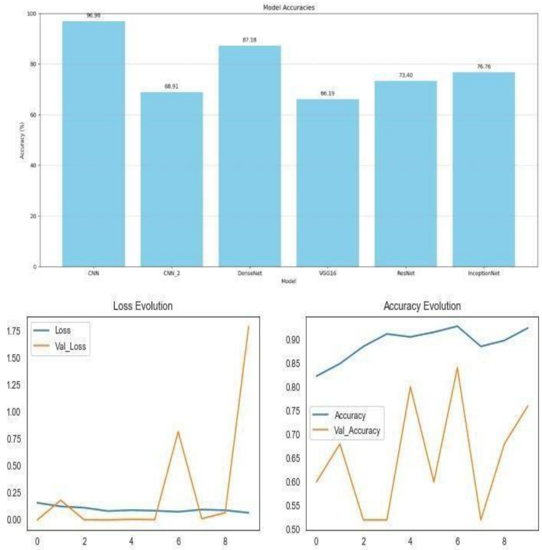

Fig 19: Comparative Analysis of Deep Learning Model Architectures

Parkinson's:

Model	Accuracy Score
Random Forest	0.824176
XgBoost	0.802198
Logistic Regression	0.791209
Gradient Boosting	0.791209
Decision Tree	0.780220
KNN	0.758242
SVM	0.516484

Fig 20: Evaluation Dashboard: Comparative Performance of Deep Learning Models

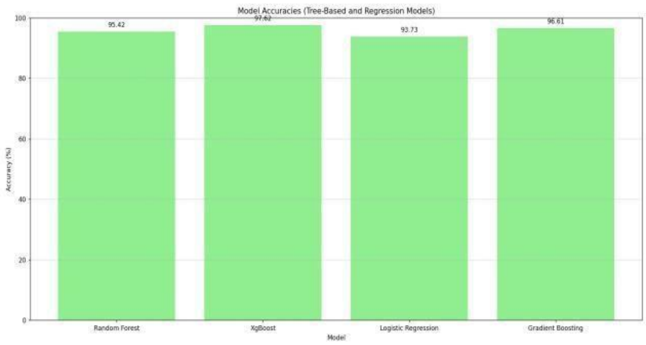

Fig 21: Comparative Accuracy of Tree-Based and Regression Models

4.2. Generative AI Layer Evaluation:

A GPT-based generative model (fine-tuned on medical literature and conversational health data) was used to:

- Communicate results conversationally.
- Explain disease risks.
- Provide health suggestions based on predictions.
- Respond to follow-up questions from users.

Participants reported a high level of satisfaction with the natural and informative responses. The conversational interface made medical feedback more digestible and engaging, particularly for non- technical users.

4.3. Use Case Observations:

- Personalization: The generative AI was capable of tailoring suggestions based on age, gender, and existing conditions, adding a personalized layer to static model outputs.
- Real-time Query Handling: Users could ask "What does this mean?", "What can I do next?", and "Is this dangerous?" – to which the system responded with medically grounded and human-like clarity.

- Limitations in Medical Nuance: While the generative model provided accurate general guidance, it occasionally avoided specificity in edge cases (e.g., rare symptoms or comorbidities), reflecting safety mechanisms and limitations in training data.

4.4. Challenges and Future Improvements:

- Medical Validation: Suggestions by the generative model should ideally be reviewed or constrained by certified healthcare data or guidelines (e.g., WHO, CDC).
- Data Privacy and Ethics: Ensuring secure handling of personal health data remains a critical aspect.
- Multilingual Support: Incorporating regional language support using multilingual LLMs can improve accessibility.

Integration with IoT Devices: Connecting wearable health trackers could make predictions and suggestions more dynamic and personalized.

5. Conclusion

The integration of generative AI with a multi-disease prediction framework significantly enhances user experience, trust, and engagement. The hybrid system not only provides accurate predictions but also bridges the communication gap between medical models and end users, paving the way for more intelligent, accessible, and user-friendly digital health tools.

References

[1] B.Hu,A.Gaurav,C.Choi,A.Almomani,Evaluatio n and comparative analysis of semantic web- based strategies for enchancing educational system development International Journal on semanticWeb and Information Systems(IJSWIS) 18 (1)(2022) 1-14

[2] Prabhavathi, K., Patil, S. (2022). “Tremors and Bradykinesia. In: Arjunan, S.P., Kumar, D.K. (eds) Techniques for Assessment of Parkinsonism for Diagnosis and Rehabilitation”. Series in BioEngineering. Springer. 135–149 https://doi.org/10.1007/978-981-16-3056-9_9

[3] X. Yao, W. Bai, Y. Ren, X. Liu, and Z. Hui, “Exploration of glottal characteristics and the vocal folds behavior for the speech under emotion,” Neurocomputing, vol. 410, no. 10, pp. 328–341, 2020

[4] G. Solana-Lavalle, J.-C. Galán-Hernández, and R. Rosas-Romero, Auto matic Parkinson disease detection at early stages as a pre-diagnosis tool by using classi ers and a small set of vocal features, Biocybern. Biomed. Eng., vol. 40, no. 1, pp. 505516, Jan. 2020.

[5] Y.Ren,H.Fei,X.Liang,D.Ji, and M.Cheng, "A hybrid neural network model for predicting kidney disease in hypertension patients based on electronic health records,"BMC Med. Informat.Decis.Mkaing,vol. 19, n0.S2,Apr.2023

[6] Saber A, Keshk A, Abo-Seida O, Sakr M (2022) Tumor detection and classification in breast mammography based on fine-tuned convolutional neural networks. IJCI Int J Comput Inf 9:74–84

[7] Navoneel Chakrabarty, “Brain MRI Images for Brain Tumor Detection Dataset” , Kaggle , April 2019

[8] S. Sharma and K. Guleria, ‘‘A deep learning based model for the detectionof pneumoniafromchestX-rayimagesusingVGG- 16andneural networks,’’ Proc. Comput. Sci., vol. 218, pp. 357–366, Jan. 2023

[9] M. Kaya and Y. Çetin-Kaya, ‘‘A novel ensemble learning framework based on a genetic algorithm for the classification of pneumonia,’’ Eng. Appl. Artif. Intell., vol. 133, Jul. 2024, Art.no. 108494, doi: 10.1016/j.engappai.2024.108494

[10] M. Ali, M. Shahroz, U. Akram, M. F. Mushtaq, S. C. Altamiranda, S. A. Obregon, I. De La Torre Díez, and I. Ashraf, ‘‘Pneumonia detection using chest radiographswithnovelEfficientNetV2Lmodel,’’I EEEAccess, vol. 12, pp. 34691–34707, 2024.

[11] Almasoud M,Ward TE.Detection of chronic kidney disease using deep learning algorithms with least number of predictors .Int J Soft Comput Appl 2023;10

[12] G.S. Monisha et al., “A Enhanced Approach for Identification of Tuberculosis for Chest X-Ray Image Using Machine Learning,” International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 11S, pp. 443-453, 2023. [CrossRef] [Publisher Link]

[13] Kahn RA, Luo Y, Wu F-X (2022) Machine learning based liver disease diagnosis: a systematic review. Neurocomputing 468:492– 509. https://doi.org/10.1016/j.neucom.2021.08.138

[14] S. Chatterjee, S. Biswas, A. Majee, S. Sen, D. Oliva, R. Sarkar, Breast cancer detection from thermal images using a Grunwald-Letnikov- aided Dragonfly algorithm-based deep feature selection method, Comput. Biol. Med. 141 (2022) 105027.

[15] Bahramiabarghouei H, Porter E, Santorelli A, Gosselin B, Popovíc M, Rusch LA (2023) Flexible 16 antenna array for microwave breast cancer detection. IEEE Trans Biomed Eng 62(10):2516–2525. https:// doi. org/ 10. 1109/TBME. 2015. 24349