

# Health Connect: AI Telemedicine Assistant

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**Abstract** - The AI-driven telemedicine application, Health Connect: AI Telemedicine Assistant, is built with an easy user interface that offers easy access to expert healthcare guidance. The application integrates with the e-Sanjeevani platform and is facilitated by a user-friendly biometric scanner, connecting users directly to medical professionals. The system combines AI diagnostics and teleconsultations, aiming to revolutionize rural healthcare. An Artificial Neural Network (ANN) model is used as the disease prediction engine, taking symptoms as inputs and predicting the most likely disease, classifying it as acute or chronic. For acute diseases, the name and medicine suggestions are provided. For chronic conditions, the user is redirected to the e-Sanjeevani portal. This application ensures quick and affordable access to quality healthcare for both rural and urban communities.

**Keywords:** Telemedicine, Disease Prediction, Machine Learning, Artificial Neural Network, Face Recognition, e-Sanjeevani.

## 1. INTRODUCTION

In the diverse tapestry of India, where modernity and tradition coexist, healthcare remains a critical challenge, particularly in rural areas. The “Health Connect: AI-Telemedicine Assistant” project is a groundbreaking endeavor designed to address disparities in healthcare access and outcomes.

Rural regions often lack basic healthcare infrastructure and skilled professionals, resulting in preventable suffering and persistent health inequalities. This project leverages artificial intelligence (AI) and telemedicine to overcome geographical barriers and bring expert medical guidance directly to rural communities.

The system uses biometric authentication for identity verification, followed by a user-friendly interface that allows patients to express their health concerns. Patients are then connected to medical professionals via the e-Sanjeevani App for virtual consultations, bridging the gap between rural and urban healthcare access.

The system goes further by offering instant disease predictions and medicine recommendations for acute conditions. For chronic diseases, users are directed to the telemedicine portal for expert consultation. This ensures timely intervention, equitable access, and reduced strain on rural healthcare systems.

## 2. MOTIVATION

The “AI-Telemedicine Assistant for Rural India” project is motivated by the significant healthcare disparities between urban and rural areas. Rural populations often struggle due to limited access to healthcare services and trained professionals,

compounded by geographical isolation.

By leveraging AI and telemedicine technologies, this project aims to reduce healthcare inequities, improve patient outcomes, and ease the burden on existing healthcare systems. Remote consultations, digital diagnosis, and last-mile delivery empower rural communities with quality healthcare access.

## 3. LITERATURE SURVEY

The survey reviews research highlighting how telehealth enables remote transmission of medical data, improves accessibility, and supports data-driven clinical decision-making. AI strengthens telemedicine by enhancing diagnosis, monitoring, and health data management. Studies emphasize the need for reliable AI-supported healthcare systems, integration of deep learning models, and validation of automated medical kiosks. Telemedicine has proven especially significant during the COVID-19 pandemic, improving patient reach and reducing medical risks. ANN architectures, IoT medical devices, and health kiosks are key enablers. Ethical considerations emphasize designing AI as an assistant, not a replacement, to maintain trust and support sustainable healthcare innovation.

## 4. PROPOSED METHODOLOGY

The proposed application ensures timely access to basic healthcare. In many parts of India, high medical costs and limited accessibility discourage timely treatment. The system aims to reduce medical expenses and promote equitable healthcare for all.

A deep learning model, specifically an Artificial Neural Network (ANN), is used for disease prediction. The ANN analyzes symptom inputs and provides accurate predictions.

### Deep Learning

Deep learning leverages multilayer neural networks to learn complex patterns from large datasets, excelling in areas like medical diagnosis and image or speech recognition. In this project, an ANN-based disease prediction model is trained on a multi-disease symptom dataset, enabling real-time, accurate predictions. By automatically extracting key features from symptoms, the model enhances diagnostic accuracy, supports rapid medical decision-making, and strengthens AI-driven telemedicine services.

### Artificial Neural Networks

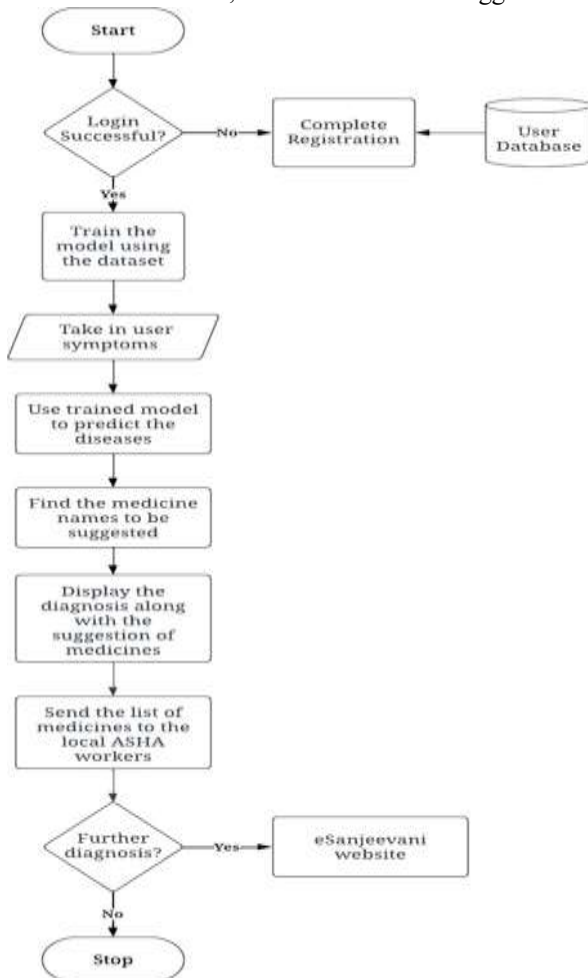
ANNs consist of neurons arranged in input, hidden, and output layers. Each neuron processes weighted inputs through activation functions, making ANNs suitable for learning complex patterns. In this system, ANNs learn symptom–disease relationships, enabling reliable disease prediction.

### Modeling and Analysis

Accuracy testing was performed using a training and testing dataset. After registration and face-recognition login, the user inputs symptoms, which are converted into binary feature vectors. These are passed to the ANN model, which predicts the top three

possible diseases and provides confidence scores.

For acute diseases, basic medicine suggestions are



displayed. For chronic diseases, users are redirected to the e-Sanjeevani portal. An SOS button is available for emergencies.

Fig 1. Workflow of the system

## 5. SYSTEM ARCHITECTURE

The system comprises:

1. User Interface
2. Face Recognition Authentication
3. ANN-Based Disease Detection
4. Telemedicine Redirection
5. SOS Emergency Module

Users authenticate using biometrics, input symptoms, and receive ANN-based predictions. Acute cases receive medicine suggestions; chronic cases are redirected for teleconsultation.

Fig. 2. System Architecture of Health Connect

ANN Disease Prediction Model

- **Input Layer:** 132 binary symptoms
- **Hidden Layers:** Dense layers with ReLU + Dropout
- **Output Layer:** 41 disease classes using Softmax

Workflow

- Face authentication
- Symptom input
- ANN prediction
- Disease classification
- Acute or chronic routing
- SOS support

## Dataset Description

The dataset is sourced from Kaggle ("Disease-Symptom Description Dataset").

### A. Dataset Files

File Name	Records	Purpose
multi disease.csv	4,920+	ANN training
shortened dataset.csv	2,000+	Testing/validation

### B. Data Content

Symptoms encoded as:

- **1 → Present**
- **0 → Absent**

41 disease classes including Dengue, Diabetes, Typhoid, Pneumonia, etc.

### C. Dataset Properties

- Total Symptoms: 132
- Total Diseases: 41
- Encoding: Binary
- Task: Multi-class classification

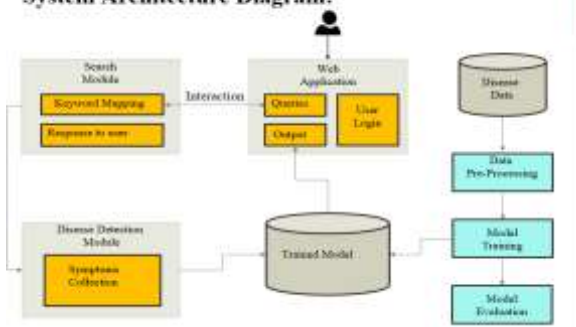
### D. Data Preprocessing

Missing values were replaced, labels encoded, and data split into 80/20 train-test sets. Data was converted into NumPy arrays before ANN training.

## 6. RESULT AND CONCLUSION

This section presents a review of different methodologies employed for the identification of symptoms and prediction of diseases. Artificial Neural Network (ANN) architecture was utilized to train a dataset and develop a system achieving high accuracy levels. It reported a success rate of 97% in accurately identifying the symptoms and predicting top three diseases based on probabilities, attributed directly to the implementation of a deep learning model. The training dataset consists of forty diseases along with their corresponding symptoms. The model uses feature selection in order to identify the symptoms of the diseases present and displays the top three diseases after matching the symptoms to the dataset. Along with this, the corresponding suggestion of

### System Architecture Diagram:



medicines is also displayed. The diagnosis is given in the form of a pie chart for better understanding as shown in the figure.

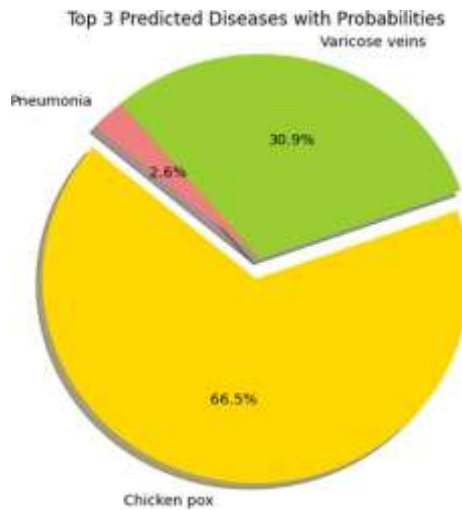


Fig 3. Top three predicted diseases based on probabilities

We visualize the training and validation accuracy to gain insights into the model's convergence behavior. Additionally, we analyze misclassified instances to identify potential areas for improvement and refinement in the model architecture and training strategy.

The 'history' object contains recorded metrics from the training process, including accuracy and loss values for both the training and validation datasets across epochs. By accessing specific keys in the 'history' dictionary and converting them into a panda DataFrame, we can plot these metrics over the training epochs.

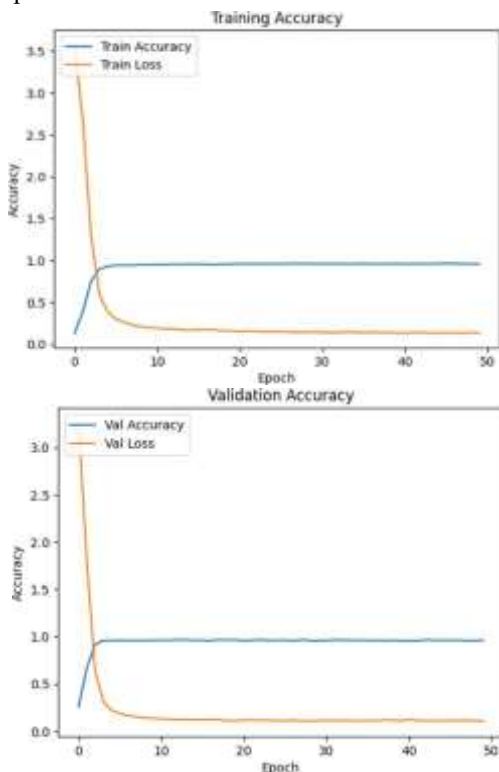


Fig 4. Training, Validation Loss and Accuracy plot

The first plot illustrates the trend of training accuracy and loss over epochs, showing how well the model is learning. Increasing accuracy indicates improvement, while a plateau or decline may suggest overfitting or convergence issues. Loss measures the difference between predicted and actual labels, with a decrease indicating better performance.

The second plot shows validation accuracy and loss. Decreasing loss and increasing accuracy indicate model improvement, while stagnation or decline may highlight overfitting. Monitoring both training and validation metrics helps identify learning issues and optimize performance.

Our research introduces a novel approach addressing gaps in existing systems. The proposed system emphasizes user-centered design and regional language support, resulting in high user satisfaction. AI integration effectively predicts diseases and recommends appropriate medicines using a comprehensive drug dataset.

The teleconsultation module connected users with certified doctors, improving access to healthcare in rural and semi-urban areas. Automated alerts helped the support team provide timely assistance, maintaining system reliability. Overall, the AI-based disease prediction and medicine recommendation were well-received, demonstrating potential for scalable digital healthcare in remote regions.

## REFERENCES

- [1] Amjad, A., Kordel, P., & Fernandes, G. (2023). A review on innovation in healthcare sector.
- [2] Maramba, I. D., Jones, R., Austin, D., Edwards, K., Meinert, E., & Chatterjee, A. The role of health kiosks: Scoping review.
- [3] Fernandes, J. (2021). Artificial intelligence in telemedicine.
- [4] Rehman, M., & Pandey, A. (2021). Review on artificial intelligence in healthcare.
- [5] Manogaran, M., & Louzazni, M. (2022). Analysis of artificial neural network: Architecture, types, and forecasting applications.
- [6] Bhaskar, S., Bradley, S., Sakhamuri, S., Moguilner, S., Chattu, V. K., Pandya, S., Schroeder, S., Ray, D., & Banach, M. Designing futuristic telemedicine using artificial intelligence and robotics in the COVID-19 era.
- [7] Agarwal, N., Jain, P., Pathak, R., & Gupta, R. Telemedicine in India: A tool for transforming health care in the era of COVID-19 pandemic.
- [8] Kustwar, R. K., & Ray, S. (2020). eHealth and telemedicine in India: An overview on the health care need of the people.
- [9] Ramgir, M. (2019). Internet of Things powered automated AI-enabled medical kiosk.
- [10] Euchner, J. (2019). Little AI, big AI—Good AI, bad AI.
- [11] Hagendorff, T., & Wezel, K. (2019). 15 challenges for AI: Or what AI (currently) can't do.
- [12] Aledhari, M., Razzak, R., Qolomany, B., & Al-Fuqaha, A. Biomedical IoT: Enabling technologies, architectural elements, challenges, and future directions.
- [13] Keirns, C. C. (2016). Health-care justice, health inequalities.
- [14] Scerbo, M. W. (2016). Simulation in healthcare. Simulation in Healthcare.
- [15] Taru, H., Sangwai, A., Shinde, V., & Sonawane, M. Enhancing medicine kiosk efficiency through AI integration. CURE A.I.