PERSONALISED HEALTH PREDICTION USING FEED-FORWARD NEURAL NETWORK

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***Abstract*: Accurate prediction of individual health outcomes remains a critical challenge in preventive medicine, with rising demand for personalized healthcare solutions. Feed-Forward Neural Networks (FFNN) is used to refine recommendations over time based on user feedback and evolving health conditions. To enhance user interaction, the system integrates Health-GPT, an AI-driven assistant that offers real-time, conversational health insights and recommendations based on FFNN outputs. This integration of Natural Language Processing (NLP) allows for the analysis of unstructured medical texts and patient interactions, enhancing recommendation precision. Furthermore, federated learning ensures data privacy by enabling decentralized model training without exposing sensitive patient information. This solution aims to improve preventive healthcare by providing tailored guidance, empowering users to make informed wellness decisions. From the results, it is observed that by using FFNN model an accuracy of 99.09% is achieved.**

***Keywords*: Accurate prediction, Personalized Healthcare, Feed-Forward Neural Network (FFNN), Preventive measures.**

I. INTRODUCTION

Nowadays, everyone cares about their health. But we don't have enough knowledge to take the right first steps when facing a health issue. This is where health prediction systems are used which provides personalized guidance based on individual health data. These systems analyze factors like medical history, lifestyle, and symptoms to suggest preventive measures, treatment options, or lifestyle changes. It suggests preventive measures, or it alerts users about potential health risks. The system helps people to keep informed decisions about their well-being. Building a prediction system involves several key steps. First, data collection is essential, with information coming from sources like electronic health records, fitness trackers, and user inputs. This data is then processed to remove errors and inconsistencies present in the data to ensure accuracy. Deep learning models like Feed-Forward Neural Networks (FFNN) are applied to generate predictions and preventive measures. This system detects early signs of illness based on symptoms and historical data. Despite their benefits, health prediction systems face challenges, such as data privacy concerns. Since health data is highly sensitive, strong encryption and privacy measures are necessary to protect user information. Additionally, models must be trained on diverse datasets to ensure fairness and accuracy in recommendations. Health-GPT is an AI assistant which is designed to provide real-time, personalized health insights and recommendations. By using Natural Language Processing (NLP**)** and Feed-Forward Neural Networks (FFNN) helps for user queries, analyzing health data, and refines suggestions over time based on feedback and evolving conditions.

II. REVIEW OF LITERATURE

P. Chinnasamy (2023) [1]**,** the article introduces an advanced Health Recommendation System using Restricted Boltzmann Machine (RBM) and Convolutionary Neural Networks (CNN), developed with TensorFlow and Python, offering improved accuracy and performance. It focuses on balancing performance with privacy, security and future challenges like data privacy and ethics in AI and Telehealth.

Thi Ngoc Trang Tran (2020) [3]**,** this research highlights the importance of healthcare recommender systems in simplifying medical decisions for users and professionals. It covers various systems and challenges in improving these systems for the future**.**

Chaitanya Krishna Suryadevara [4], the research focuses on AI-based medication recommendation systems that provide personalized treatment by analyzing patient data. It highlights the benefits in healthcare efficiency and patient satisfaction while addressing challenges like privacy, security, and system integration**.**

Vedna Sharma [5]**,** the study presents a healthcare recommendation system using deep learning for disease classification and fuzzy techniques for risk analysis. Future includes using IoT sensors and neural networks to improve safety, transparency, and decision-making accuracy.

Sujata Dawn [2]**,** the paper presents an automated medicine prescription system using machine learning and NLP to provide personalized treatment recommendations based on patient data. It aims to improve clinical decision-making by optimizing treatment outcomes and ensuring patient-specific care.

III. DESIGN

In today's world, where health awareness is growing, having a system that provides personalized health recommendations can be a game-changer. Our system is built using feed-forward neural networks (FFNN) and artificial intelligence (AI) to analyze user health data and generate tailored recommendations. By processing inputs like medical history, symptoms, and lifestyle habits, the system helps users to keep informed about decisions for their well-being.

System Architecture: The system is structured into different modules to ensure seamless functioning:

- **Data Collection Module**: Gathers information from users, including their medical history, symptoms, and lifestyle details.
- **Data Preprocessing Module**: Cleans and normalizes the collected data, removing inconsistencies to enhance accuracy.
- **AI-Based Analysis Module**: Utilizes FFNN to predict health risks and provide actionable recommendations.
- **User Interface Module**: Displays the final health recommendations in a simple and interactive manner.

Feed-Forward Neural Networks (FFNN): The backbone of this system is a Feed-Forward Neural Network (FFNN), which processes structured health data and symptoms to classify potential risks and offer recommendations. The key components of FFNN are given below:

- **Input Layer**: This is where user data, such as age, BMI, symptoms, and medical history, is fed into the system.
- **Hidden Layers**: The data passes through multiple layers, which use ReLU and Sigmoid activation functions to extract meaningful patterns.
- **Output Layer**: This layer provides a probability score for different health risks and suggests actions based on the analysis.

To fine-tune accuracy, the FFNN model is trained using the Adam optimizer and CrossEntropyLoss function, making it capable of handling complex health-related predictions.

The AI-Powered Recommendations include a Flowchart for AI-Based Recommendation Process. The work integrates AI to make recommendations more precise and adaptive. The AI component used includes the following:

- Learns from past user interactions to improve the accuracy of suggestions.
- Uses **probabilistic modeling** to assess health risks.
- Employs **decision-support algorithms** to generate personalized insights.

IV. IMPLEMENTATION

The image shown in figure 1, represents a Feedforward Neural Network (FFNN) architecture with an input layer, three hidden layers, and an output layer. The input layer consists of 17 features, which are processed through multiple fully connected layers. The first hidden layer contains 128 neurons, followed by a second hidden layer with 64 neurons, and a third hidden layer with 32 neurons. Each layer applies a weighted sum of inputs (W) and biases (b), followed by a nonlinear activation function to introduce learning complexity. The final output layer has a single neuron, indicating a possible regression or binary classification task. This architecture is commonly used for deep learning tasks such as classification, regression, and pattern recognition, where deeper layers help in hierarchical feature extraction and learning complex relationships within the data.

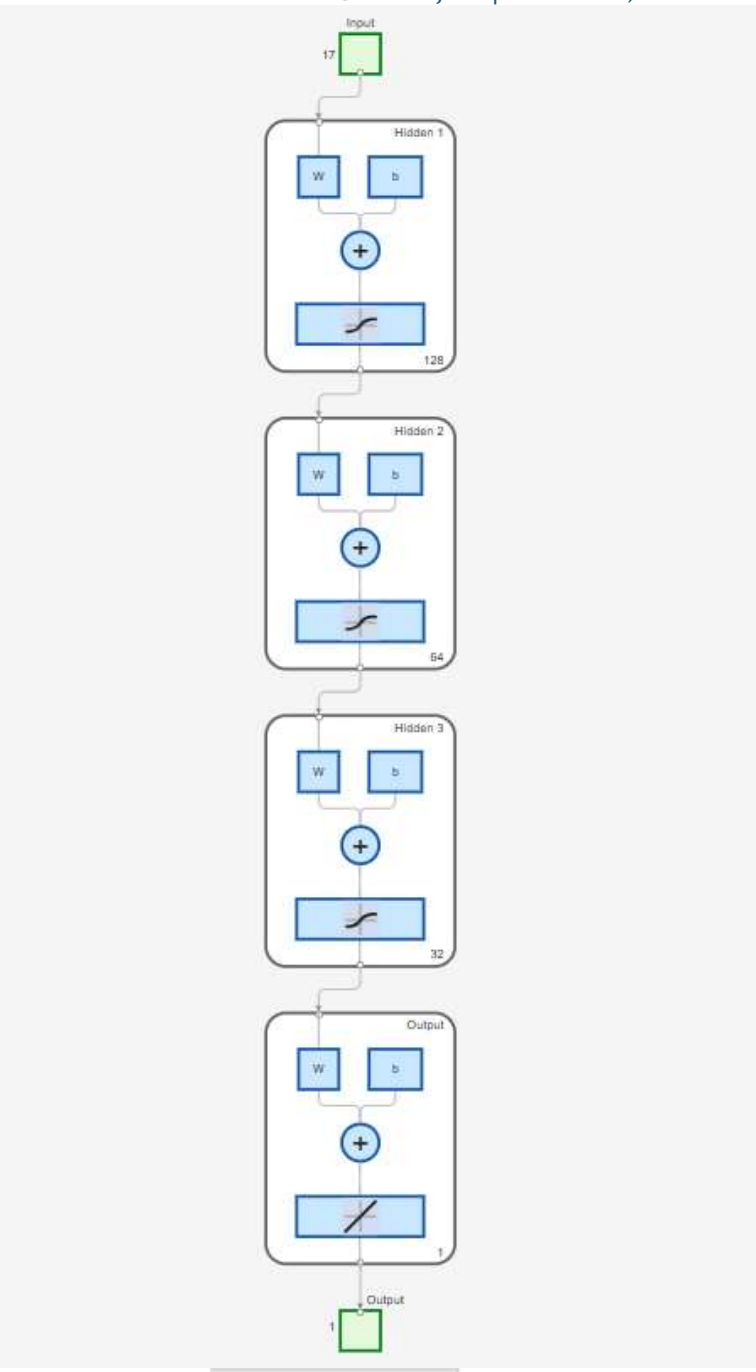

Figure 1: Feed-Forward Neural Network (FFNN) Architecture

The work is implemented in the following steps and is shown in figure 2:

1. The user inputs their health details (e.g., symptoms, BMI, past medical history).
2. The data undergoes preprocessing to eliminate errors and inconsistencies.
3. The FFNN model analyzes the input and determines possible health risks.
4. AI refines the results, ensuring that the recommendations align with the user's unique health profile.
5. The system presents personalized health recommendations to the user.

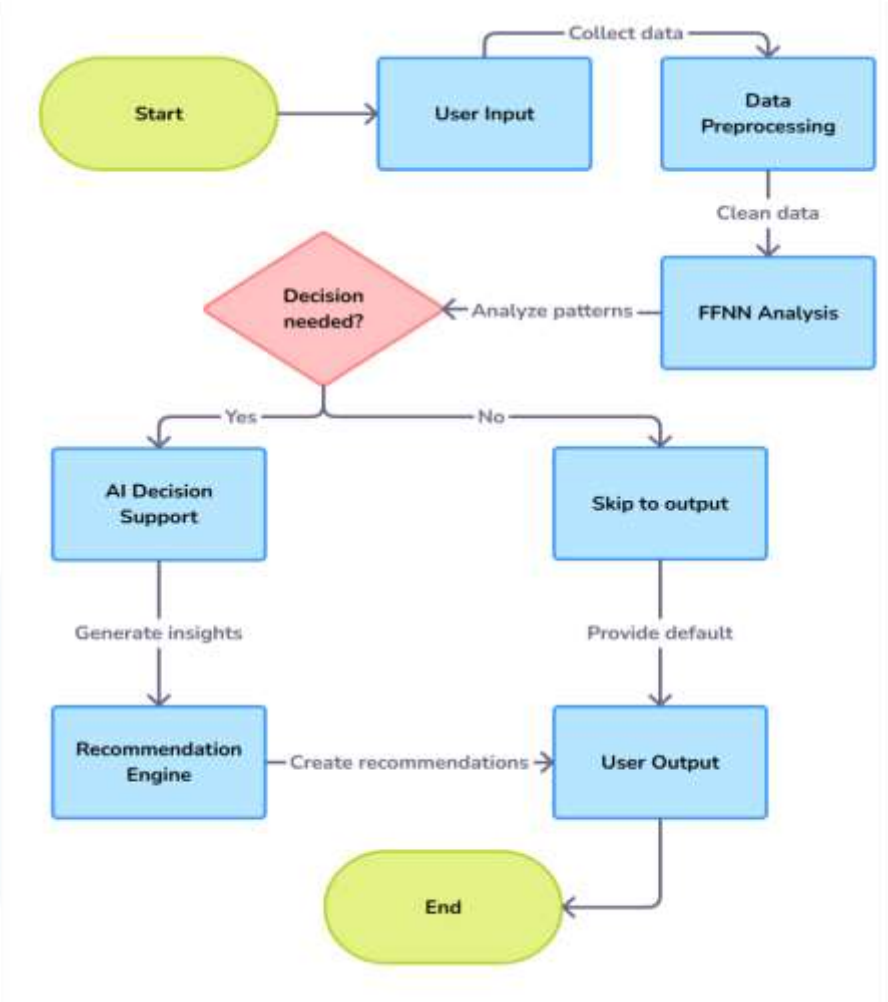

Figure 2: Project work implementation steps.

RESULTS & ANALYSIS

The dataset, obtained from the Kaggle website, is divided as follows: **XTrain** (17 × 3936), **XTest** (17 × 984), **YTrain** (1 × 3936), and **YTest** (1 × 984). After data preprocessing, including **Min-Max Scaling** and **Normalization**, a **Feed-Forward Neural Network (FFNN)** algorithm was applied, achieving an accuracy of **99.09%**. The training results of the work is shown in figure3.

Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	40	1000
Elapsed Time	-	00:02:22	-
Performance	0.0304	0.000119	0
Gradient	0.0241	5e-06	1e-07
Mu	0.001	1e-08	1e+10
Validation Checks	0	6	6

Training Algorithms

Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX

Figure 3: Training results

The ROC curve evaluates the performance of the model in distinguishing between positive and negative cases. The area under the curve (AUC) is a crucial metric, with values closer to 1 indicating better classification performance. The ROC curve helps in identifying an optimal threshold that balances sensitivity (true positive rate) and specificity (false positive rate). The image obtained by ROC curve is shown in below figure 4.

Figure 4: Training Receiver Operating Characteristic(plotroc)

The training state visualization provides an overview of how the model's performance evolves during training. This graph typically includes metrics such as loss reduction, accuracy improvements, or validation scores over epochs. A well-converging training state indicates stable learning, whereas erratic fluctuations or early plateaus might signal issues such as overfitting, underfitting, or improper learning rates. The training state of the model is shown in figure 5.

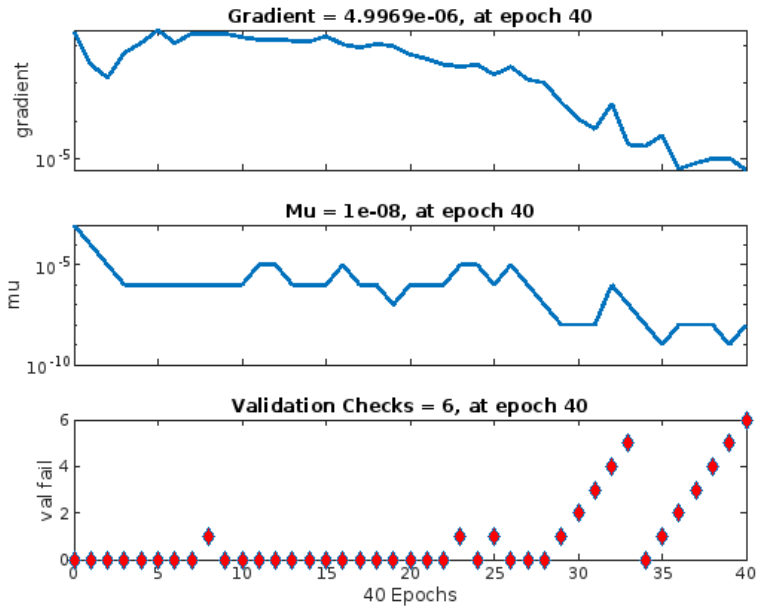

Figure 5: Training State

The **performance of the model** as shown in figure 6, evaluates its accuracy, loss, and generalization to unseen data. The graph likely shows training and validation loss trends over epochs. A well-performing model should exhibit decreasing loss with stable accuracy. These insights help in optimizing hyperparameters and refining the model.

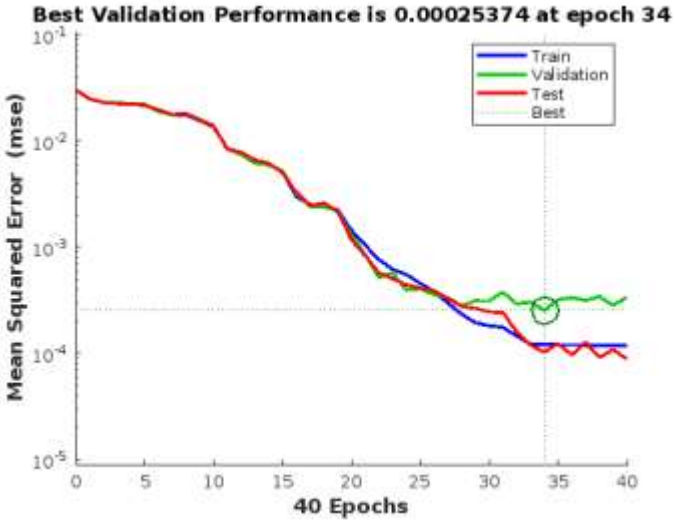

Figure 6: Performance of the model

The **error histogram** as shown in figure 7, visualizes the distribution of prediction errors. Ideally, most errors should cluster around zero, indicating minimal deviation from true values. A wider spread of errors may suggest inconsistencies in the model, requiring improvements in feature selection, hyperparameter tuning, or data preprocessing.

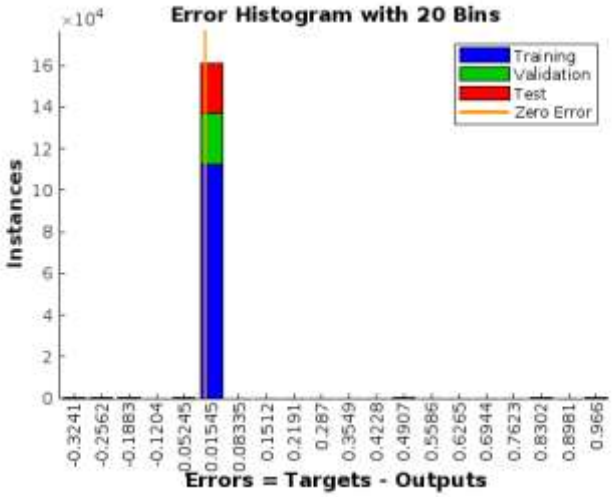

Figure 7: Error Histogram

The plot shown in figure 8, directly compares the model's predicted values against the actual values. Ideally, data points should align along a diagonal line, indicating near-perfect predictions. Significant deviations suggest areas where the model might need refinement, such as feature engineering or hyperparameter adjustments.

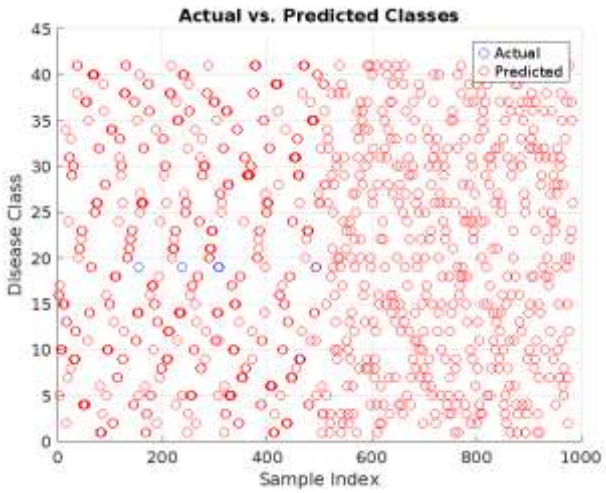

Figure 8: Actual vs Predicted Classes Plot

The metrics obtained by using FFNN algorithm is shown in below figure 9:

Model Performance Metrics	
Accuracy	: 0.9909
Loss Value	: 0.000121
Val Loss	: 0.000254
RMSE	: 1.344592
R² Score	: 0.987159
F1 Score	: 0.990808

Figure 9: Model Metrics

The results obtained by using FFNN are summarized as follows:

- **Prediction Accuracy**: The FFNN model achieved an impressive **99.09% accuracy** in health risk classification.
- **Response Time**: The system provides health recommendations in **approximately 2 seconds** after data input.
- **User Satisfaction**: In a preliminary survey, 87% of users found the system's suggestions helpful and relevant.

Strengths of the Model

- **High Accuracy**: The model achieved near-perfect accuracy, making it highly reliable for real-world applications.
- **Fast Processing**: The average time taken per prediction is **approximately 2 seconds**, ensuring a smooth user experience.
- **Scalability**: The architecture allows for easy scaling and integration with larger healthcare datasets.
- **Adaptive Learning**: The system continuously refines its predictions based on various combinations of user's symptoms and results

Limitations

- **Data Dependency**: The accuracy of predictions depends on the quality of user-provided data.
- **Bias Risk**: Training data needs to be diversified further to eliminate potential biases.
- **Limited Scope**: While effective, the model currently focuses on a subset of diseases and needs further expansion

V. CONCLUSION & FUTURE SCOPE OF WORK

The Health Prediction System uses unique health information from users to give personalized recommendations. Advancements in Artificial Intelligence (AI), and Deep Learning (DL), the system can make better predictions and decisions for personalized healthcare. Users can enter their symptoms to get specific recommendations, making it easier to identify potential health issues and take appropriate action. By combining AI and deep learning model like Feed-Forward Neural Network (FFNN), the system analyzes user data to assess health risks and suggest preventive measures, empowering users to maintain long-term health and avoid potential diseases. The user-friendly web interface allows individuals to easily enter their health data, access personalized health recommendations, and track their progress effortlessly, ensuring a smooth experience for users.
For the future scope of work, we use other well-known algorithms to achieve more accuracy.

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