

Analysis and Implementation of Multimodal Gait Recognition Using Logistic Regression for Neurodegenerative Diseases

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ABSTRACT—Gait analysis is an important clinical tool for assessing motor function in neurodegenerative diseases such as Parkinson's disease (PD), Huntington's disease (HD), and Amyotrophic Lateral Sclerosis (ALS). Traditional clinical evaluation methods are often subjective and may fail to detect subtle gait abnormalities. To address these limitations, this work proposes a multimodal gait recognition system that integrates both deep learning and machine learning techniques along with FPGA-based implementation. The system utilizes two datasets: the NDD dataset, which includes force-sensing and time-interval signals, and the PD gait dataset, which consists of acceleration and vertical ground reaction force (VGRF) data. A Spatial Feature Extractor (SFE) is employed to extract statistical features from the input signals, followed by a Correlative Memory Neural Network (CorrMNN) autoencoder for feature compression. Temporal dependencies are captured using a Bidirectional Long Short-Term Memory (Bi-LSTM) network, and a multiswitch mechanism is applied for effective feature selection. The refined features are then classified using multiple machine learning models, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Logistic Regression. Among these, Logistic Regression is implemented on a PYNQ-Z2 FPGA using a custom AXI-based IP core for real-time inference. Experimental results demonstrate high classification performance, validated using accuracy analysis, confusion matrix, and ROC curves. The proposed system effectively classifies gait patterns into Healthy, PD, HD, and ALS categories, providing a robust and efficient solution for real-time clinical decision support.

Index Terms - Gait, Parkinson's disease (PD), Huntington's disease (HD), Amyotrophic Lateral Sclerosis (ALS), multimodal gait recognition,

Correlative Memory Neural Network (Corr-MNN), machine learning models, FPGA.

I. INTRODUCTION

Neurodegenerative diseases (NDDs) are a group of disorders characterized by the progressive loss of neurons, which affects motor and cognitive functions. Since human gait is controlled by the central nervous system, any damage to motor neurons leads to abnormal walking patterns. Therefore, gait analysis plays a significant role in understanding movement disorders and in the early diagnosis of neurodegenerative diseases. Patients with different NDDs exhibit unique gait characteristics. For example, Parkinson's disease (PD) is associated with shuffling steps, reduced stride length, and freezing of gait, while Huntington's disease (HD) shows irregular and uncoordinated movements due to chorea. Amyotrophic Lateral Sclerosis (ALS) primarily affects motor neurons and leads to muscle weakness, stiffness, and spastic gait patterns. These variations in gait can be used as important biomarkers for disease identification and severity analysis, as discussed in the base work.

In recent years, automated gait analysis has gained significant attention due to advancements in sensor technologies such as cameras, wearable accelerometers, force sensors, and 3D skeleton tracking systems. These systems provide objective and quantitative measurements of gait patterns compared to traditional clinical observation methods, which are often subjective. However, many existing approaches rely on single-modality data, which may fail to capture the complete characteristics of gait. Since gait variations between different diseases are often subtle, it is necessary to use multimodal data to improve classification accuracy.

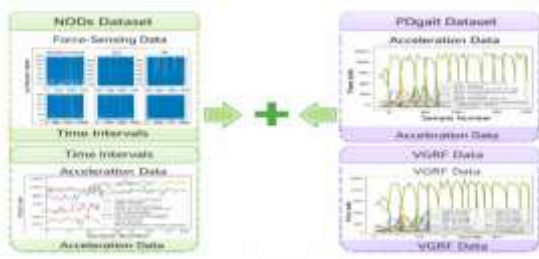


Fig. 1. Multimodal gait datasets used in this work. Dataset 1 (NDDs) consists of force-sensing data and time interval signals, while Dataset 2 (PDgait) includes acceleration data and vertical ground reaction force (VGRF) signals for analyzing gait patterns of PD, HD, ALS, and healthy subjects.

In this work, two different multimodal gait datasets are used for analysis, as shown in Fig. 1. The first dataset (NDDs dataset) includes force-sensing data and time interval signals, which capture variations in stride timing and pressure distribution across different subjects. The second dataset (PDgait dataset) consists of acceleration signals and vertical ground reaction force (VGRF) data, which provide detailed information about joint movements and force variations during walking. These datasets collectively provide complementary spatial and temporal information required for accurate gait analysis and disease classification.

To address these challenges, a multimodal gait recognition system is proposed that combines data from multiple sources to capture both spatial and temporal characteristics of gait. Inspired by the base model, this work uses a Spatial Feature Extractor (SFE) to extract spatial features and a Correlative Memory Neural Network (CorrMNN) to learn temporal relationships. A Bidirectional Long Short-Term Memory (BiLSTM) network is used to further model sequential dependencies, and a multiswitch mechanism enhances feature selection for improved classification performance.

In addition to deep learning, machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Logistic Regression are used to classify gait patterns into different disease categories. Among these models, Logistic Regression is selected for hardware implementation due to its simplicity and efficiency. The trained model weights are converted into fixed-point representation and implemented on a Field-Programmable Gate Array (FPGA) using a custom AXI-based IP core.

The main objective of this work is to develop an efficient and real-time gait recognition system that integrates

multimodal data, advanced learning techniques, and FPGA-based hardware acceleration. The proposed system enables accurate classification of PD, HD, ALS, and healthy subjects, making it suitable for clinical decision support and continuous monitoring applications.

II. RELATED WORK

In recent years, gait recognition has become an important research area for the diagnosis of neurodegenerative diseases (NDDs) such as Parkinson's disease (PD), Huntington's disease (HD), and Amyotrophic Lateral Sclerosis (ALS). Existing research mainly focuses on two categories: 1) single-modal gait recognition and 2) multimodal gait recognition systems.

A. Single-Modal Gait Recognition

Single-modal gait recognition uses data from a single sensor such as vision systems, inertial sensors, or force sensors to analyze walking patterns. Earlier studies have used camera-based systems and depth sensors to extract skeletal information for gait analysis. These approaches provide useful spatial information, such as joint positions and body posture, but they do not capture important temporal characteristics like stride intervals and walking speed.

To overcome this limitation, several machine learning and deep learning techniques have been applied to time-series gait data. Models such as Support Vector Machine (SVM), regression models, and neural networks have been used to classify gait patterns and detect abnormalities. In addition, force-based data such as Vertical Ground Reaction Force (VGRF) and acceleration signals from wearable sensors have been widely used for analyzing subtle changes in gait. These methods are effective in capturing specific aspects of gait; however, they are limited because they rely only on a single type of data and cannot fully represent complex gait behavior in neurodegenerative diseases.

B. Multimodal Gait Recognition

To improve performance, recent research has focused on multimodal gait recognition, where multiple data sources such as force sensors, acceleration signals, and visual data are combined. Multimodal approaches provide both spatial and temporal information, leading to better classification accuracy compared to single-modal methods. Deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been used to extract spatiotemporal features from multimodal data.

However, many existing multimodal approaches do not effectively capture the correlation between different data sources. In addition, most of these systems are implemented only in software and are not optimized for real-time deployment. Furthermore, limited work has been done to integrate multimodal gait analysis with hardware acceleration platforms such as FPGA.

C. Proposed Work

To address the limitations of existing gait analysis methods, this work proposes a multimodal gait recognition system that combines both deep learning and machine learning techniques along with FPGA implementation. The system uses two types of datasets: the NDD dataset, which includes force-sensing data and time interval signals, and the PD gait dataset, which consists of acceleration and vertical ground reaction force (VGRF) data. Initially, a Spatial Feature Extractor (SFE) is applied to extract statistical features from both datasets. These extracted features are then passed to a Correlative Memory Neural Network (CorrMNN) autoencoder, which compresses the high-dimensional feature vector into a lower-dimensional representation while preserving important information. To capture temporal dependencies in gait patterns, the compressed features are further processed using a Bidirectional Long Short-Term Memory (BiLSTM) network, and a multiswitch mechanism is used to select important features and reduce irrelevant information. The refined features are then classified using multiple machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Logistic Regression. Among these models, Logistic Regression is selected for hardware implementation on an FPGA using a custom AXI-based IP core, enabling real-time processing. The proposed system effectively integrates multimodal data, advanced learning models, and hardware acceleration to improve classification accuracy and provide reliable detection of gait conditions, including Healthy, Parkinson's Disease (PD), Huntington's Disease (HD), and Amyotrophic Lateral Sclerosis (ALS).

III. PROPOSED METHOD

In order to achieve accurate gait recognition for neurodegenerative disease patients and healthy subjects, a multimodal framework is proposed for spatial feature extraction, temporal feature learning, classification, and real-time hardware deployment. The proposed system combines two different gait datasets and processes them through a sequence of software and hardware stages.

First, multimodal gait signals from the NDD and PD gait datasets are supplied to a Spatial Feature Extractor (SFE) for statistical feature generation. Next, the extracted feature vector is compressed using a Correlative Memory Neural Network (CorrMNN) autoencoder. The compressed representation is then passed to a Bidirectional Long Short-Term Memory (BiLSTM) network to learn temporal dependencies in gait patterns. After temporal modeling, a multiswitch mechanism is applied to refine the learned features by selecting the most relevant information for classification. The refined features are then classified using multiple machine learning models, namely Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Logistic Regression. Finally, Logistic Regression is implemented on the PYNQ-Z2 FPGA platform using a custom AXI-based IP core for real-time disease classification. The final output of the system is one of four gait classes: Healthy, Parkinson's disease (PD), Huntington's disease (HD), or Amyotrophic Lateral Sclerosis (ALS).

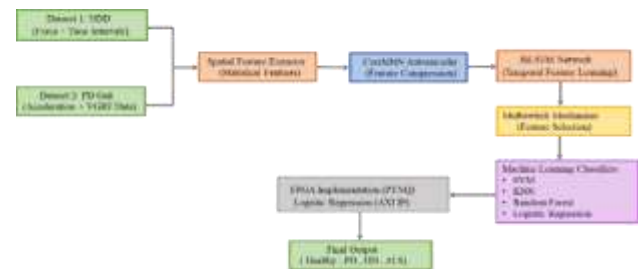


Fig. 2. Overall block diagram of the proposed multimodal gait recognition system for classification of Healthy, Parkinson's disease (PD), Huntington's disease (HD), and Amyotrophic Lateral Sclerosis (ALS).

The overall framework of the proposed system is shown in Fig. 2. The system takes two multimodal datasets as input. The first dataset is the NDD dataset, which contains force-sensing data and time interval signals. The second dataset is the PD gait dataset, which includes acceleration data and vertical ground reaction force (VGRF) signals. These two data sources provide complementary gait information and improve the ability of the system to capture both static and dynamic walking characteristics.

The complete processing pipeline consists of the following major stages: 1) spatial feature extraction, 2) feature compression, 3) temporal feature learning, 4) feature selection, 5) machine learning classification, and 6) FPGA implementation. In this way, the proposed framework acts as an end-to-end multimodal gait recognition system that integrates software-based model learning with hardware-based deployment.

1. Spatial Feature Extractor (SFE)

The first major component of the proposed system is the Spatial Feature Extractor (SFE). In this stage, the raw gait signals from both datasets are converted into numerical features that describe the statistical properties of the gait patterns. The SFE computes features such as mean, standard deviation, minimum, maximum, median, percentiles, variance, and first-order difference statistics from each signal channel.

Let the gait signal be represented as

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

where x_i denotes the signal value at the i^{th} sample and n is the total number of samples. The mean and standard deviation are calculated as

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2}$$

where μ is the average value of the signal and σ represents the spread of the signal values. Similarly, other descriptive features are computed and concatenated to form a fixed-length spatial feature vector. In the implemented system, the final feature vector is standardized to a length of 200 by padding or truncation, which ensures a uniform input size for the subsequent deep learning model.

Thus, the output of this stage is the spatial feature vector

$$F_{sp} \in \mathbb{R}^{200}$$

which is supplied to the CorrMNN autoencoder.

2. CorrMNN Autoencoder for Feature Compression

After spatial feature extraction, the feature vector is passed to the CorrMNN autoencoder for feature compression. The purpose of this block is to reduce the high-dimensional feature vector into a compact latent representation while preserving the most important gait information.

The encoder part of the autoencoder transforms the input feature vector into a lower-dimensional space through multiple dense layers, while the decoder reconstructs the original input during training. The encoder can be written as

$$h = f(Wx + b)$$

where x is the input feature vector, W is the weight matrix, b is the bias term, and $f(\cdot)$ is the activation function. The compressed latent representation is given by

$$z = f(W_h h + b_h)$$

where z is the bottleneck feature vector. In the proposed implementation, the input dimension is reduced from 200 to 128 through the encoder. The decoder reconstructs the input vector as

$$\hat{x} = g(W_z z + b_z)$$

where $\hat{x}$ is the reconstructed output and $g(\cdot)$ is the decoder activation function.

The autoencoder is trained using the reconstruction loss

$$L = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2$$

where L is the mean squared error between the original input and reconstructed output. This stage helps remove redundancy and noise from the extracted spatial features and produces a compact 128-dimensional latent representation for temporal modeling.

3. BiLSTM Network for Temporal Feature Learning

The compressed latent features obtained from the CorrMNN autoencoder are then processed by a Bidirectional Long Short-Term Memory (BiLSTM) network. Since gait is a sequential process, temporal modeling is required to capture stride patterns, walking rhythm, and step-to-step variations.

In the BiLSTM network, the sequence is processed in both forward and backward directions. The forward hidden state is represented as

$$\vec{h}_t = \text{LSTM}(x_t)$$

and the backward hidden state is represented as

$$\overleftarrow{h}_t = \text{LSTM}(x_t)$$

where x_t is the input at time step t . The final hidden representation is obtained by concatenating the forward and backward states as

$$h_t = [\vec{h}_t, \overleftarrow{h}_t]$$

This bidirectional processing enables the network to learn both past and future contextual information from

gait sequences, improving the model's ability to identify temporal abnormalities associated with PD, HD, and ALS.

4. Multiswitch Mechanism for Feature Selection

After temporal feature learning, the output of the BiLSTM network is refined using a multiswitch mechanism. This block acts as a gating-based feature selection unit that emphasizes important features and suppresses irrelevant information.

The multiswitch operation can be expressed as

$$g = \sigma(Wx)$$

$$y = x \cdot g$$

where x is the BiLSTM output, W is the learnable weight matrix, g is the gating vector, $\sigma(\cdot)$ is the sigmoid activation function, and y is the refined feature output. By selectively weighting the features, the multiswitch mechanism improves the discriminative power of the feature representation before classification.

Machine Learning Classifiers

The refined features obtained from the deep learning model are further classified using multiple machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and Logistic Regression. These classifiers are used to evaluate performance and identify the most suitable model for gait recognition.

1) Support Vector Machine (SVM)

SVM is used to find an optimal hyperplane that maximizes the margin between different classes. To handle nonlinear data, the Radial Basis Function (RBF) kernel is employed, which maps the input data into a higher-dimensional space. The decision function of SVM is given by:

$$f(x) = w^T x + b$$

where w is the weight vector, x is the input feature vector, and b is the bias term. The classification rule is:

$$y = \text{sign}(w^T x + b)$$

where $y \in \{-1, +1\}$ represents the class label.

The RBF kernel is defined as:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$$

where γ is the kernel parameter and $\|x_i - x_j\|^2$ is the Euclidean distance.

2) K-Nearest Neighbors (KNN)

KNN is a simple and effective classification method that assigns a class label based on the majority of the nearest neighbors. The Euclidean distance used for similarity measurement is:

$$d(x, x_i) = \sqrt{\sum_{j=1}^n (x_j - x_{i,j})^2}$$

where x is the test sample, x_i is the training sample, and n is the number of features. The predicted class is given by:

$$\hat{y} = \text{mode}(y_1, y_2, \dots, y_k)$$

where k is the number of nearest neighbors.

3) Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees to improve classification accuracy and reduce overfitting. The prediction is computed as:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(x)$$

where T is the number of trees and $h_t(x)$ is the output of the t^{th} tree. The final classification is obtained using majority voting:

$$\hat{y} = \text{majority vote}(h_1(x), h_2(x), \dots, h_T(x))$$

4) Logistic Regression

Logistic Regression is used for probabilistic classification. It computes the probability of each class and selects the class with the highest probability. The linear model is given by:

$$z = Wx + b$$

The softmax function is used to compute probabilities:

$$P(y = k) = \frac{e^{z_k}}{\sum_j e^{z_j}}$$

The predicted class is:

$$\hat{y} = \arg \max P(y)$$

Among all classifiers, Logistic Regression is selected for hardware implementation due to its simplicity and suitability for FPGA deployment.

F. FPGA Implementation on PYNQ-Z2

The final stage of the proposed system involves implementing Logistic Regression on the PYNQ-Z2 FPGA board. The trained weights and bias values from the software model are extracted and converted into fixed-point representation. These values are stored in memory files and utilized in a custom AXI-based IP core. The FPGA computes class scores using the following equation:

$$\text{Score}_k = \sum_{i=1}^n x_i \cdot w_{k,i} + b_k$$

where x_i is the input feature, $w_{k,i}$ is the weight corresponding to class k , and b_k is the bias term. The final predicted class is determined as:

$$\text{Class} = \arg \max (\text{Score}_k)$$

The FPGA implementation enables real-time inference with low latency and reduced power consumption. The output corresponds to one of the four classes: Healthy, Parkinson's disease (PD), Huntington's disease (HD), or Amyotrophic Lateral Sclerosis (ALS).

G. Final Output

The final output of the proposed system is the classification of gait data into one of the following categories: Healthy, Parkinson's Disease (PD), Huntington's Disease (HD), Amyotrophic Lateral Sclerosis (ALS). Thus, the proposed framework integrates multimodal data processing, spatial feature extraction, deep learning-based temporal modeling, machine learning classification, and FPGA-based deployment into a unified system for accurate and efficient gait recognition.

IV. EXPERIMENTAL RESULTS

A. Dataset and Training Details

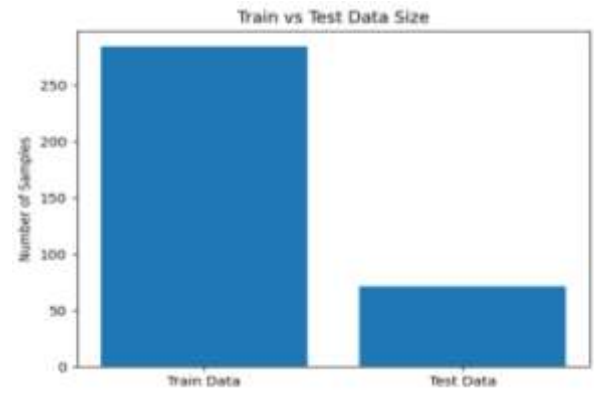


Fig.3. Train and test data size.

The Fig.3 shows the distribution of training and testing data used in the proposed system. The dataset is divided into two parts, where the training data consists of a larger number of samples compared to the testing data. The training dataset is used to train the deep learning and machine learning models so that they can learn important features and patterns from the gait data. The testing dataset contains fewer samples and is used to evaluate the performance of the trained model on unseen data. This type of data distribution helps the model to learn effectively and improves its generalization ability. Overall, the graph indicates that the dataset is properly split, which supports accurate and reliable gait-based classification of diseases such as Healthy, Parkinson's, Huntington's, and ALS.

The proposed system is evaluated using two datasets, namely the NDD dataset and the PD gait dataset. The total number of samples used in this work is 355, which includes Healthy, Parkinson, Huntington, and ALS classes. Since the dataset is imbalanced, the SMOTE technique is applied to balance all classes equally. After balancing, each class contains 171 samples, which improves the training performance.

The model is trained using both deep learning and machine learning techniques. The CorrMNN autoencoder is trained for feature compression, followed by a deep model for temporal learning. The extracted features are then used to train machine learning models such as SVM, KNN, Random Forest, and Logistic Regression.

B. Training and Validation Performance



Fig.4. Training and validation accuracy of the proposed deep learning model over multiple epochs.

The Fig.4. shows the performance of the deep learning model over multiple epochs. Initially, the training accuracy increases steadily from around 60% to above 90%, indicating that the model is learning useful features from the input data. As the number of epochs increases, the training accuracy stabilizes near 97–99%, which shows strong learning capability.

The validation accuracy shows some fluctuations in the early epochs due to dataset complexity and variability in gait patterns. This is mainly because the model is trying to generalize across different classes such as Healthy, PD, HD, and ALS. However, after several epochs, the validation accuracy improves significantly and reaches values close to 95–100%, indicating good generalization performance. Although there are some sudden drops in validation accuracy at certain epochs, the overall trend shows improvement and stability. This behavior suggests that the model is not overfitting heavily and is capable of learning meaningful spatiotemporal features from multimodal gait data. Overall, the graph demonstrates that the proposed deep learning model achieves high training and validation accuracy, making it suitable for gait classification tasks.

C. Models Accuracy Comparison

Models	Accuracy	Precision	Recall	F1-Score
SVM	0.85	0.80	0.73	0.76
KNN	0.81	0.70	0.73	0.71
Random Forest	0.84	0.78	0.68	0.72
Logistic Regression	0.87	0.78	0.81	0.79
Deep Model	0.88	0.79	0.86	0.82

Fig. 5. Accuracy comparison of different machine learning and deep learning models for multimodal gait classification.

The Fig.5. shows the accuracy comparison of different models used in this work. The Deep Learning model

achieves the highest accuracy of 88%, which indicates its ability to learn complex spatiotemporal gait features. Among machine learning models, SVM and Random Forest show similar performance (~85%), and Logistic Regression achieves high accuracy (~87%), while KNN achieves slightly lower accuracy (~81%). Based on these results, Logistic Regression is selected for FPGA implementation due to its simplicity and efficient hardware execution.

D. Confusion Matrix



Fig.6. Confusion matrix of the proposed model for classification of Healthy, Parkinson, Huntington, and ALS gait patterns.

The Fig.6. represents the classification performance of the proposed system for four classes: Healthy, Parkinson, Huntington, and ALS. From the matrix, it can be observed that the model correctly classifies most of the samples in each category.

For the Healthy class, 19 samples are correctly classified, while a few samples are misclassified as Parkinson and ALS. In the case of Parkinson, 39 samples are correctly classified, which shows that the model performs very well for this class, with only a few misclassifications into the Healthy class.

For the Huntington class, 3 samples are correctly classified, while one sample is misclassified as Healthy. This is mainly due to the smaller number of samples available for this class. Similarly, for the ALS class, two samples are correctly classified.

Overall, the confusion matrix shows that the model achieves high accuracy for dominant classes like Parkinson and Healthy, while performance for minority classes such as Huntington and ALS is comparatively lower. This is mainly due to class imbalance and limited training samples for these categories.

E. ROC Curves

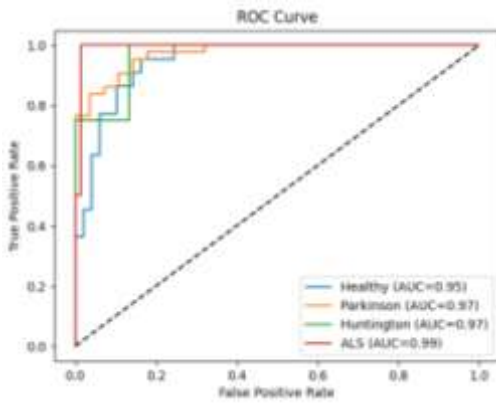


Fig. 7. ROC curve showing classification performance for Healthy, Parkinson, Huntington, and ALS classes.

The Fig.7. shows The ROC curve represents the performance of the proposed model for different classes such as Healthy, Parkinson, Huntington, and ALS. It shows the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR).

From the graph, it is observed that all classes achieve high AUC values, indicating good classification performance. The ALS class achieves the highest AUC value of 0.99, which shows excellent discrimination capability. The Parkinson and Huntington classes achieve AUC values of 0.97, indicating strong performance. The Healthy class achieves an AUC value of 0.95, which is also very good. The ROC curves are closer to the top-left corner, which indicates that the model has high sensitivity and specificity. This shows that the proposed system can effectively distinguish between different gait patterns of neurodegenerative diseases. the ROC analysis confirms that the model provides reliable and accurate classification results for all classes.

Hardware Results:

The hardware implementation of the proposed system was successfully validated on the PYNQ-Z2 FPGA board as shown in Fig.8. The trained Logistic Regression model was deployed as a custom AXI-based IP core, and input gait feature values were provided through the Jupyter Notebook interface. The FPGA processes the input features in real time and generates a 2-bit classification output, which is displayed using onboard LEDs. Each LED corresponds to a specific condition:

LED0 indicates Healthy, LED1 indicates Parkinson's disease, LED2 indicates Huntington's disease, and LED3 indicates ALS.

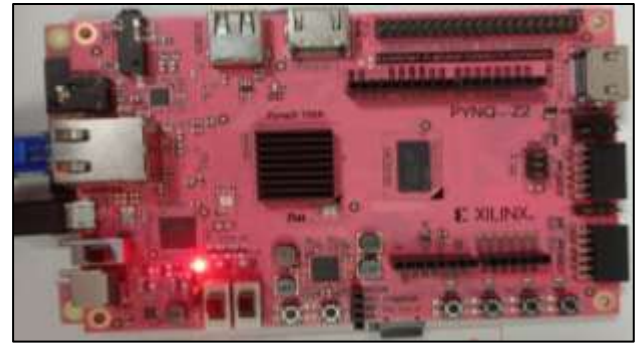


Fig.8. PYNQ-Z2 FPGA.

The experimental results demonstrate that the system correctly identifies the input condition with low latency, confirming efficient hardware, software integration and real-time disease classification capability.

V. CONCLUSION

In this work, a multimodal gait recognition system is developed for the classification of neurodegenerative diseases such as Parkinson's disease, Huntington's disease, and ALS by using NDD and PD gait datasets. The system applies spatial feature extraction, deep learning, and machine learning techniques to achieve accurate classification of gait patterns. The results show that the deep learning model provides the highest accuracy, while machine learning models such as SVM, Random Forest, and Logistic Regression also give stable performance. Logistic Regression is selected for FPGA implementation, and the trained model is successfully deployed using a custom AXI-based IP on the PYNQ-Z2 board for real-time processing. Overall, the proposed system provides an efficient and reliable solution for gait-based disease detection and can be useful for clinical applications, and in future work, performance can be improved by using larger datasets and advanced models.

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