FPGA-based Hardware Classifier for Diabetic Sensorimotor Polyneuropathy Severity Assessment

Sandeep Kumar Pandey[1], Geetika Srivastava[1], Mamun Bin Ibne Reaz[2], Sawal Hamid Md Ali[2], Edi Kurniawan[3], Rabindra Gandhi Thangarajoo[2], Ganga Ram Mishra[1], SacchidaNand Shukla[1]

[1]*Dr. Rammanohar Lohia Avadh University, Ayodhya, India*
[2]*Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia*
[3]*National Research and Innovation Agency (BRIN) of Indonesia, KST BJ Habibie, South Tangerang, Indonesia*

Abstract

At present Diabetic Sensorimotor Polyneuropathy (DSPN) is a fast growing condition among diabetic patients, with potentially severe consequences such as permanent disability and leaving to death in some cases. However, there is hope on the horizon as early detection can prevent the amputation and deaths. Present study proposes an innovative solution for early detection of DSPN severity by the application of Machine Learning (ML) techniques over Electromyography (EMG) signals obtained from various lower limb muscles during gait. These signals provide valuable information about the nerve function and enable us to identify the presence of DSPN at an early stage. To bring this technology to life, a sophisticated neural network is further implemented on a hardware platform Xilinx ZCU102 Field Programmable Gate Array (FPGA) device. The outcomes are promising, with the device accuracy rate of approximately 79% in detecting DSPN. This outcome may pave way for a brighter future in DSPN diagnosis. With continued advancements, this technology has the potential to transform the DSPN diagnosis process in near future, allowing for earlier intervention and better patient outcomes.

Keywords

DSPN, EMG, FPGA, ML

1. Introduction

Diabetes has emerged as a concerning and chronic disease, leading to permanent disabilities and, unfortunately, even loss of life among patients. One of the disturbing actions of diabetes is the rise of Diabetic Sensorimotor Polyneuropathy (DSPN) severity, a prevalent condition affecting individuals worldwide [1]. DSPN serves as an early warning sign for diabetic foot ulcers and non-healing wounds [2, 3]. Nearly, about half of diabetic patients suffer from DSPN, and shockingly, half of them are unaware of the symptoms [4, 5]. Statistics reveal that 34% of diabetic patients experience pain sensations, with type 2 diabetes patients exhibit a higher incidence of painful neuropathic symptoms compared to type 1 diabetes patients. These painful symptoms not only impact physical and psychological functioning but also contribute to anxiety and depression.

The diagnostic methods for DSPN, such as Vibration Perception Threshold (VPT), Nerve Conduction Studies (NCS), Neuropathy Disability Score (NDS), Michigan Neuropathy Screening Instrument, Achilles tendon reflexes, pinprick and temperature sensation, are expensive, require expertise, and, in some cases, cause discomfort [6]. While there have been notable advancements in treating symptomatic pain with the use of drugs, therapeutic options targeting

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sandeep.avadh@gmail.com (S. K. Pandey); geetika_gkp@rediffmail.com (G. Srivastava)
https://dblp.org/pid/158/4439.html (G. Srivastava)
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the underlying pathophysiology of DSPN remain limited. Early detection and prevention play crucial roles in effectively managing DSPN [7].

To address these challenges, authors proposed an approach: designing a DSPN severity classifier using Machine Learning (ML) and its hardware implementation. Popularity of ML techniques in biosignal processing making them ideal for DSPN diagnosis purpose [8]. Since DSPN primarily affects lower limb muscles [9], therefore Electromyography (EMG) signals are collected from various lower limb muscles during gait and processed using a ML algorithm. This allows us to develop a DSPN severity classifier, which is then implemented in hardware using the Xilinx ZCU102 FPGA board. Implemented hardware provided satisfactory accuracy during testing. In our literature study we found that many studies reported approximately 99% accuracy in software-based approaches, but as per research resources available no hardware implemented algorithm has reported such high accuracy. Proposed work paves the way for the development of a patient-friendly, portable device that can accurately classify patients as normal or abnormal without the need for extensive expertise or complex procedures.

The remaining part of the paper is organized as follows: discussion about EMG signal pre-processing and processing using ML algorithms, proposed method, dataset preparation process, design of the neural network, results and discussion and conclusion.

2. EMG Signal Pre-Processing

Electromyography (EMG) is a valuable technique used to study the electrical signals generated by muscles in the body. By using electrodes, EMG pattern records and measures the electrical activity produced by different muscles, providing information about their functions and behavior [10]. In the recording process of EMG signals, two significant factors greatly impact signal quality: the signal-to-noise ratio and distortion [10, 11, 12]. Addressing these factors is important to ensure accurate and reliable results. For this, a meticulous approach towards signal pre-processing is essential. Figure 1 show the key steps involved in the pre-processing of EMG signals, which plays important role in improving the quality of the recorded EMG signal.

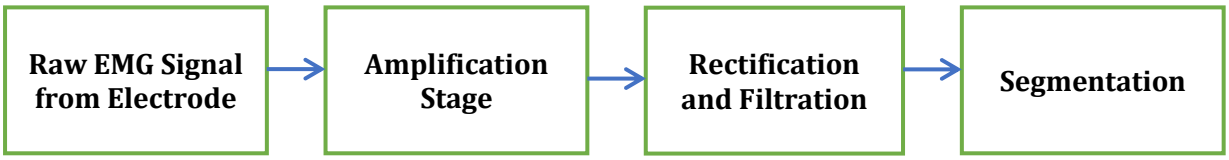

Figure 1: EMG Signal Pre-Processing Stage

The initial stage involves the collection of raw EMG signals using electrodes and their amplification. Usually, a differential amplifier is used to amplify the signals properly. The raw signal may be prone to various types of noise, such as low or high-frequency interferences, as well as other artifacts. To overcome these unwanted disturbances, various processing techniques are applied to minimize noise and artifacts. Since the amplitude of the EMG signal is mostly used by researchers and clinicians, therefore further processing steps are used to extract relevant information. The signal is rectified to change it into a unidirectional waveform, allowing the analysis of the absolute magnitude of the EMG signal. Additionally, Averaging techniques are used to obtain a representative measure of the EMG amplitude, providing important information about muscle activity. In this way recorded EMG signal is preprocessed to ensure good quality for interpretation and analysis.

3. EMG Signal Processing Using Machine Learning

EMG signal processing using ML algorithms involves several steps to extract meaningful features from it and then classify the signals accurately. Figure 2 shows the stages of EMG signal processing using ML [13, 14, 15].

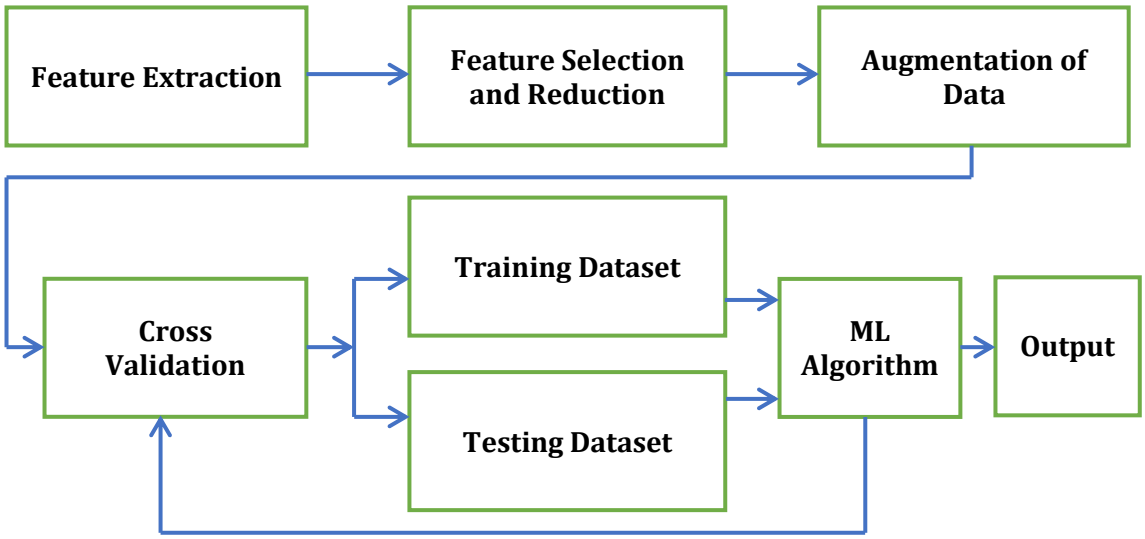

Figure 2: EMG signal processing by using Machine learning

3.1. Feature Extraction

Feature extraction is an important step in EMG signal processing, as it involves capturing the relevant information that can be used for categorization. Various time-domains, frequency-domain, or time-frequency domain features are extracted using feature extraction techniques for processing.

3.2. Feature Selection

The extracted features may contain redundant or irrelevant information. Feature selection methods employed to identify the most discriminative features that contribute to classification accuracy. This step helps reduce the dimensionality of data and thereby reduces the computational complexity.

3.3. Data Augmentation

It is a technique of artificially increasing the number of data in training set by generating modified copies of dataset from existing data. It is important for AI applications, as accuracy increases with the amount of training data.

3.4. Training Data Preparation

The pre-processed and normalized features are paired with corresponding labels (class annotations) to create a labeled training dataset.

3.5. Machine Learning Algorithm Selection

Popular ML algorithms are used for EMG signal classification, such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Random Forests, or Deep Learning models like Convolutional Neural Networks (CNN) [16]. In proposed work SVM is selected due to its ability to handle complex decision boundaries and neural networks due to its power of computational capabilities.

3.6. Model Training

The ML algorithm is trained on the DSPN dataset to learn the patterns and relationships between the features and the corresponding classes.

3.7. Model Evaluation

After training, the performance of the trained model is evaluated using separate validation or testing datasets. Cross-validation technique is used to obtain more reliable performance estimates.

3.8. Testing and Deployment

The designed model is tested on new, unseen EMG signal data to assess its generalization ability. Then final trained model deployed in real-world applications to classify EMG signals and aid in the diagnosis or monitoring of conditions of DSPN.

4. Proposed Method

Inspired by the work of Muthuramalingam et al. [17], the presented study developed a novel approach for DSPN diagnosis using a linear Support Vector Machine (SVM) based bi-layered neural network. This architecture offers the advantage of efficient resource utilization while achieving promising results with respect to accuracy. In proposed method, the first step involved is training the SVM using MATLAB, freezing the model and then proceed for hardware implementation. The SVM was trained on the DSPN training dataset, learning to classify EMG signals associated with DSPN. SVM provided weighted outputs that captured the discriminative characteristics of the input signals. To further enhance the accuracy of diagnostic system, the weighted outputs from the SVM integrated into a bi-layered neural network. The bi-layered neural network takes the weighted outputs of the SVM as inputs and processes them to generate the final diagnostic output.

5. Dataset Preparation

During the gait cycle, lower limb muscles, namely the Vastus Lateralis (VL), Gastrocnemius Lateralis (GL), and Tibialis Anterior (TA), are particularly affected [18]. To conduct the study on Diabetic Sensorimotor Polyneuropathy (DSPN) diagnosis, the EMG data was obtained from the research conducted by Watari et al. [19]. The dataset comprised 142 samples from 29 patients without DSPN (considered as the normal condition) and 72 samples from 14 patients with severe DSPN (considered as the abnormal condition) and did not include samples from patients with mild or moderate DSPN. To ensure a balanced representation of normal and abnormal cases, the Synthetic Minority Over-sampling Technique (SMOTE) data augmentation technique [20, 21] was utilized. By applying SMOTE, the number of samples for the abnormal conditions increases, bringing them to an equal proportion in the training dataset. By applying Relief feature selection algorithm [22] on the EMG data obtained from the GL, VL, and TA muscles, identify the most significant features from each dataset, highlighting the specific aspects of muscle activity that are indicative of DSPN. Total 19 significant features identified from each dataset, as illustrated in Figures 3, 4, and 5.

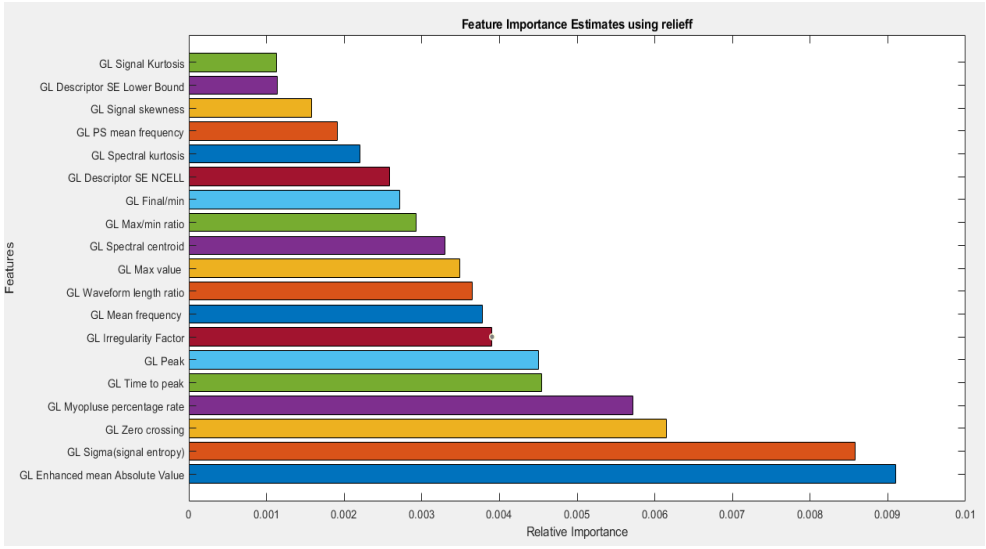

Figure 3: GL Extracted Feature Using Relief Method

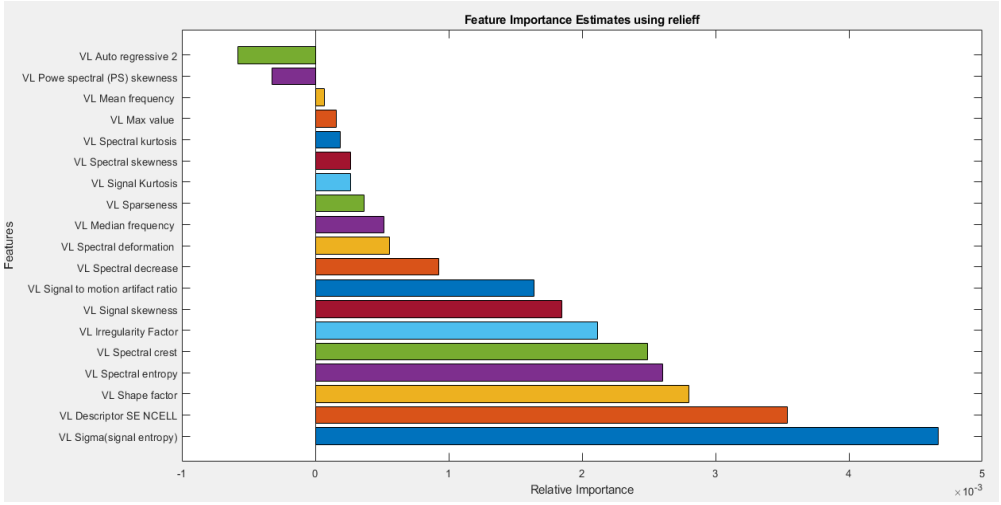

Figure 4: VL Extracted Feature Using Relief method

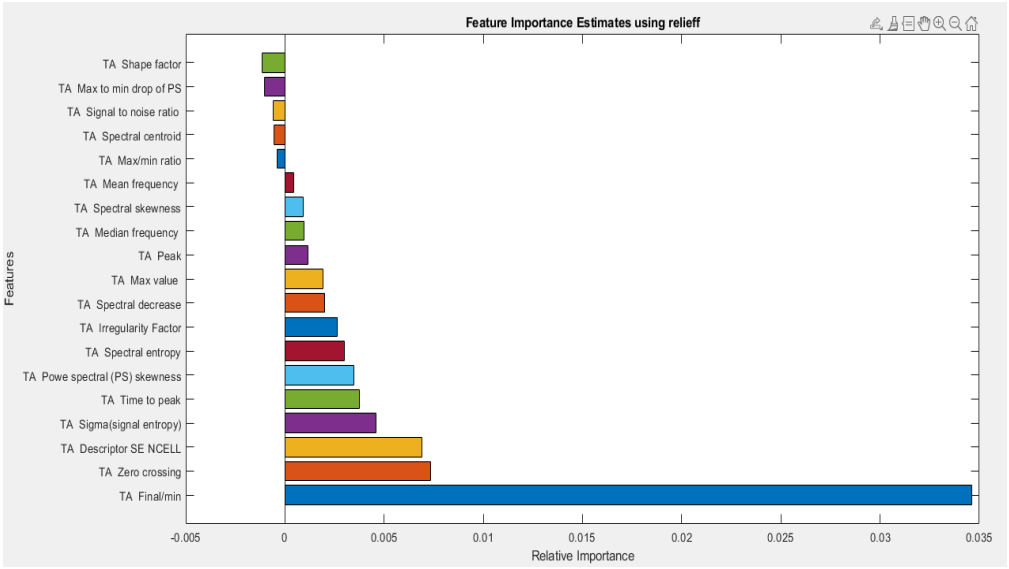

Figure 5: TA Extracted Feature Using Relief Method

The SVM classifier was trained using MATLAB 2021. For training total nine features selected to represent the EMG data. These features were chosen using Relief feature selection techniques. For the Gastrocnemius Lateralis (GL) data, the three most significant features selected were GL Enhanced mean Absolute Value, GL Sigma (signal entropy) and GL Zero crossing. Likewise, for the Vastus Lateralis (VL) data, the three most significant features chosen were VL Sigma (signal entropy), VL Descriptor SE NCELL and VL Shape factor. Finally, for the Tibialis Anterior (TA) data, the three most significant features included were TA Final/min, TA Zero crossing and TA Descriptor SE NCELL. Using this set of nine features, trained a linear SVM model in MATLAB, which exhibited an accuracy of 82% approximately. The trained SVM model allowed us to classify the EMG data accurately based on the selected features and their corresponding weights. This weighted output, which encapsulates the discriminative information learned by the SVM, serves as valuable input to the neural network for further analysis and classification.

6. Neural Network Design

Using the weighted output from the SVM a bi-layered neural network was designed in MATLAB. This neural network played a crucial role in further refining the classification process for DSPN diagnosis. In proposed work, this MATLAB-based neural network achieved an accuracy of approximately 80%. To extend the applicability of this ML algorithm, it was implemented in hardware using Vivado Design Suite (version 2022.2) provided by Xilinx. The neural network's hardware implementation was realized using the Xilinx ZCU102 FPGA board. This comprehensive hardware integration provided the full potential of the neural network's computational capabilities in a practical and real-time manner. Figure 6 shows the architecture of hardware-implemented neural network.

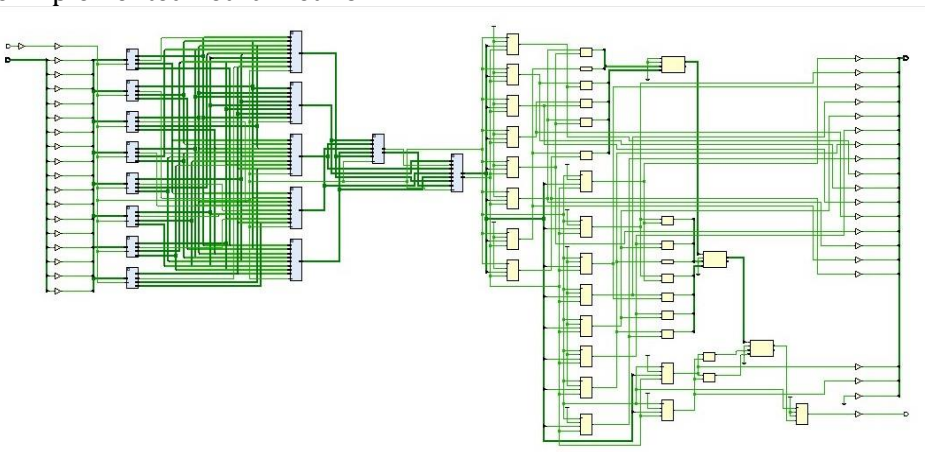

Figure 6: Neural Network Schematic Design in Vivado

Additionally, the device package is shown in Figure 7, which encapsulates the hardware implementation of DSPN severity classifier.

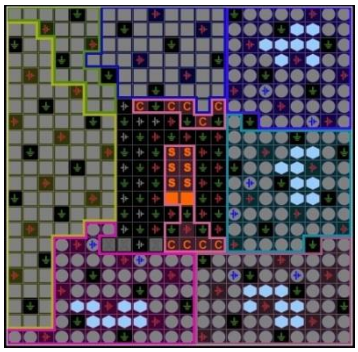

Figure 7: Device Package

The proposed study bridges the gap between software and hardware by successfully translating MATLAB-based neural network into a practical and tangible device. This model brings us one step closer to a future where improved diagnostic device can assist in the early detection and prevention of DSPN.

7. Result and Discussion

The hardware implementation of DSPN severity classifier on the ZCU102 FPGA board resulted in an accuracy of approximately 79% while effectively utilizing the available resources. The satisfactory performance across various metrics like power and latency signifies the potential of proposed approach in diagnosing DSPN in patients. Although current implementation focused on classifying patients into DSPN and non-DSPN categories, but there are more categories in DSPN severity such as mild, moderate and sever. This opens up avenues for future improvements and upgrades in hardware design. Table 1 presents a resource utilization report, showing the efficient utilization of resources in presented hardware implementation. Additionally, Figure 8 provides a graphical representation of the percentage utilization of resources, showing optimal resource allocation.

Table 1
Resource Utilization Summary

Name	Total	Utilization
LUTs	274080	1468
Register	548160	128
F7 Muxes	137040	188
BRAM Tiles	912	147
DSPs	2520	74
Bonded IOB	328	49

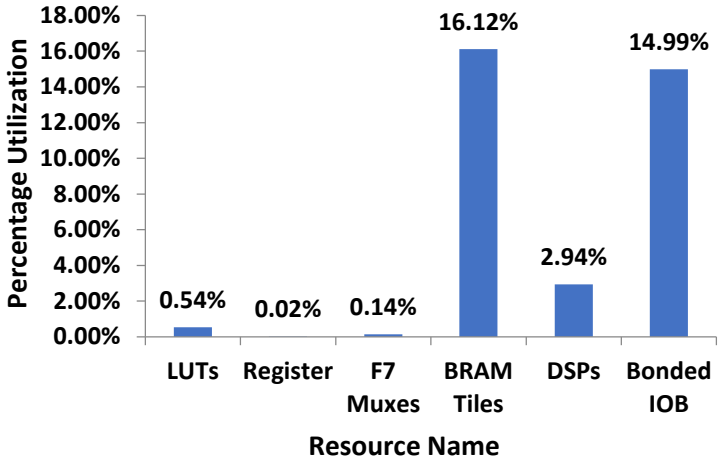

Figure 8: Resource Utilization Report

8. Conclusion and Future Work

Early diagnosis plays an effective role in preventing the severity of Diabetic Sensorimotor Polyneuropathy (DSPN). To accomplish this, a machine learning-based model has been successfully hardware implemented on the Xilinx ZCU102 FPGA board. Implemented model achieved accuracy of 79% approximately in binary class classification, indicating its potential

for early diagnosis of DSPN. While design's accuracy is moderate, it should be more to ensure good quality diagnosis and also the device should classify the severity level. Presented study encourages to design a model in near future that can identify DSPN patients and also assess the severity level of their disease. This will enable medical professionals to provide targeted interventions and personalized treatment plans.

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