OPEN ACCESS
International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-12 Issue-2, July 2023

Classification of Emotion using Eeg Signals: an FPGA Based Implementation

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***Abstract:** An electroencephalograph is a device that records all electrical energy in the human brain using wearable metal electrodes placed on the skull. Electrical impulses connect brain cells and are always mobile, even at rest. This activity appears as a squiggly line in EEG recordings. Activity gaze data is pre-processed to a frequency range of 0 to 75 Hz. This creates a new matrix with a sample rate of 200 Hz and a range of 0-75 Hz. A finite-impulse-response low-pass filter was used because the bandpass would distort his EEG data after processing. Each pre-processed EEG signal has an output that completes the feature extraction process. Principal Component Analysis or PCA is passed in the feature reduction phase. PCA is an analytical process that uses singular value decomposition to transform a collection of corresponding features into mutually uncorrelated features or principal components. Principal component analysis: (a) mean normalization of features (b) covariance matrix (c) eigenvectors (d) reduced features or principal components. The above steps are passed to the SVM classifier for sentiment output. His VHDL code and testbench for 2*2 matrices were written, waveforms and RTL schemes were created in Xilinx 14.5. For the FPGA implementation, a Simulink model was designed, and the eigenvalues were pre-determined using a system generator.*

***Keywords:** Electroencephalography (EEG), Autonomous Nervous System (ANS), Principal Component Analysis (PCA), Support Vector Machine (SVM).*

I. INTRODUCTION

According to psychology, emotion recognition is the attribution of emotional states based on the observation of visual and auditory nonverbal cues. Emotions are essential in our daily life and work. Evaluating and adjusting emotions in real-time enriches and improves people's lives. Emotional recognition. Another example is that when caring for patients, especially those with facial expression problems, doctors can provide better care if they are aware of their actual emotional state. Emotional detection using EEG has attracted considerable interest in recent years. This is an essential aspect of the brain-computer interface system (brain-computer interface), which significantly improves human-machine communication. The most common classification relates to the frequency bands of the EEG waveform, which allows EEG signals to be classified into five different frequency bands. Therefore, five separate frequency bands and their associated mental health are described below.

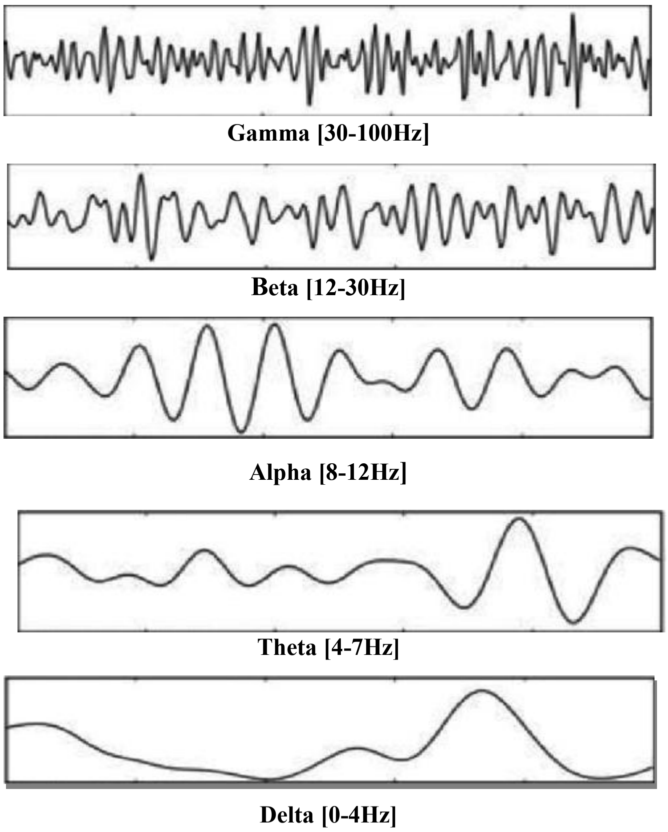

Figure 1: Different frequency bands of EEG signals

GAMMA (30-100Hz): These waves are the elevated frequency bands, and the range is by far the widest. This may be difficult to measure, as the elevated frequency of the small amplitude makes the signal easily contaminated by the muscles surrounding the head.

BETA (12-30Hz): These waves are "fast" waves of activity. It is best seen from the front and is often observed bilaterally in a symmetrical distribution. Sedatives and sleeping pills, especially benzodiazepines and barbiturates, increase this value. It is widely accepted as a natural beat. This is the dominant rhythm when the patient is alert, anxious, or even has his eyes open.

Manuscript received on 07 June 2023 | Revised Manuscript received on 01 July 2023 | Manuscript Accepted on 15 July 2023 | Manuscript published on 30 July 2023.
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ALPHA(8-12Hz): This is the first electroencephalogram discovered. Some studies compare alpha valves to creativity. This is the main rhythm observed in typically relaxed people. It is present for most of life, especially shortly after age 13.
THETA (4-8Hz): These waves are the "Slow" waves of activity. Lesions: A pear sign indicates focal specific brain lesions; it can also be prevalent in diffuse diseases, such as metabolic encephalopathy or hydrocephalus.

II. RELATED WORKS

It is not an easy task for organizers to observe the engagement level of a video meeting audience. This research was conducted to build an intelligent system to increase the experience of video conversations, such as virtual meetings and online classrooms, using a convolutional neural network (CNN) and a support vector machine (SVM) [1]. This study presents an electroencephalogram (EEG)-dependent hardware system architecture for instantaneous emotion recognition based on polyphasic convolutional neurons. Network Algorithm (CNN) running on a 28nm technology chip and Field Programmable Gate Array (FPGA) for binary and quaternary partitions [2]. In this work, we propose an improved deep convolutional neural network model for emotion classification using a discrete training method that combines convolutional features of lower, middle, and upper layers [3]. In this paper, Facial feature vectors in dual form are obtained using a basic binary pattern histogram by tracing the bins in clockwise and anti-clockwise direction using the SVM binary and multi-class technique [4]. Digital predistortion is a baseband signal transformation approach that effectively mitigates impairments in RF power amplifiers. This technique is attained using the Cordic square root algorithm for FPGA implementation [5]. The real-time SVM-dependent emotion recognition algorithm comprises four distinct steps to achieve emotion detection. This is done using an adapted histogram of oriented gradients (HoG) algorithm and an SVM algorithm [6]. In this project, the EEG-based emotion identification is done using an SVM classifier, and the electroencephalogram is used as it is a non-invasive, portable, inexpensive device [7]. In this project, a recently developed emotional detection structure dependent on a recording feed in real time is employed by employing a support vector machine (SVM), which is a reliable classification algorithm [8]. In this project, a deep convolutional neural network model, EEGNet, Vivado and its hardware implementation, have been evolved for obtaining generalization towards different BCI Paradigms for designing portable EEG-based BCIs [9]. The technique used in this work is a feature trial using SVM to distribute emotions and a modern approach of preprocessing in the structure of local secular pattern, which was then used to feed to the SVM classifier model [10]. The Haar attribute by Viola and Jones is the earliest real-time frontal-view face detector and is proposed in this project. In this paper, the authors propose the use of Haar-like features and AdaBoost categorisation to detect faces. Support Vector Machine (SVM) is the classifier used in this system [11]. In this paper, they have used a multilayer perceptron and an artificial neural network (MLP-ANN) for the classification of an FPGA-based embedded system [12].

A. Research Issues Identified

- We need to train on a large amount of data, which is not easy.
- Precision when the flag has to be classified into five recurrence groups.
- Issues in exact feeling acknowledgement.

B. Motivation

- Acknowledgements arrangements require a parcel of information to be prepared.
- Incorrect feeling pointers.

C. Objectives

- To recognize human feelings.
- To reduce the information dimensionality in expansion to make enhancements to the classification process.
- To achieve exactness utilizing an SVM
- To actualize a feeling acknowledgement on an FPGA

III. PROPOSED METHODOLOGY

A. Software Methodology

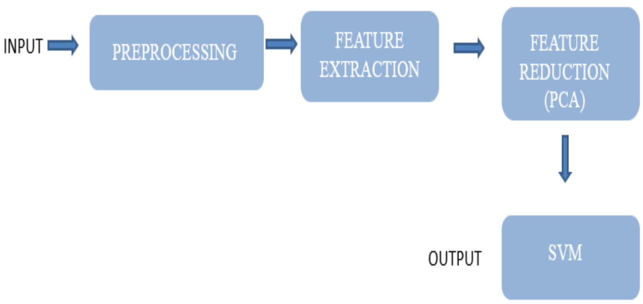

Figure 2: Proposed Software Methodology

(1) Preprocessing:
Preprocessing is implemented on the raw dataset to filter the data and obtain a clean dataset by checking for missing values and scaling the facial expression frames to enhance their quality. This step creates a new matrix with a sampling frequency of 200Hz, and we utilised the 'Low Pass Filter' to decimate the highest frequency range above 75Hz.
(2) Feature Extraction:
During the Feature Extraction Process, we applied the wavelet filter bank technique to separate the preprocessed inputs into different frequency sub-bands. This also reduces the complexity of the data by dividing the frequency range into high-pass and low-pass results, which are then filtered to obtain the targeted bandwidths for further processing.
(3) Feature Reduction:
Principal Component Analysis, abbreviated as PCA, is the most widely used technique for dimensionality reduction. It transforms the correlated features in the data into orthogonal components, thus capturing all the primary information while reducing its dimensionality. PCA steps:(1) Mean Standardisation, (2) Computing co-variance, (3) Computing Eigen Vectors to identify principal components, (4) Creating feature vectors.

Retrieval Number: 100.1/ijrte.B78080712223
DOI: 10.35940/ijrte.B7808.0712223
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(4) SVM (Support Vector Machine):
SVM is a familiar Supervised Machine Learning Algorithm. The goal of the SVM algorithm is to obtain a hyperplane in an N-dimensional space that uniquely categorises the features. Additionally, it handles both classification and regression on linear and non-linear data.

B. Implementation For FPGA

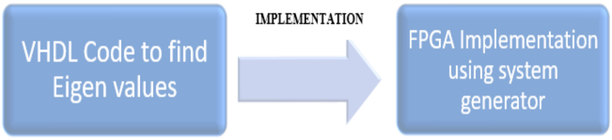

Figure 3: Proposed Hardware Methodology

A test bench was written in Xilinx 14.5 to determine the eigenvalues of a 2*2 matrix using VHDL (Very High-Speed Integrated Circuit Hardware Description Language) and the CORDIC (Coordinate Rotating Digital Computer) square root algorithm. VHDL code is Loaded into a black box to obtain the output of eigenvector calculations by Simulink. Additionally, I utilised System Generator to design the hardware block.

IV. EXPERIMENTAL RESULTS & DISCUSSIONS

A. Dataset Collection

The SEED dataset consists of EEG (Electroencephalogram) data from 15 subjects who watched 15 Chinese film clips, each evoking emotions such as positive, neutral, and sad. The data was stored in 45 MATLAB files with a downsampling rate of 200 Hz. A bandpass filter of 0-75 Hz was being utilized for pre-processing. EEG signals arising were recorded using 62 62-channel ESI Neuro Scan System. Fifteen Chinese film clips, involving positive, negative, and neutral emotions, were presented to each of fifteen Chinese subjects randomly. The duration of each clip was 4 minutes. The experimental procedures initially include 5-second hints, followed by a 4-minute clip, then a 45-second self-assessment, and finally 15 seconds of rest.

B. Experimental Procedure

By creation, human beings are the only emotional animals. They are triggered and activated by emotions. Emotions are the drivers of human behaviour, as they determine what is essential and what is inessential. Obtaining human emotions from the face instantly may lead to errors, as humans may try to conceal their genuine emotions. Using physiological methods, such as electroencephalography (EEG), can help overcome the drawbacks. The first step is to select records. Use a seed dataset. It consists of 45 MATLAB files, each with 10 functions and 62 channels. The data is then pre-processed to remove noise and facilitate the classification of the input data. In the feature extraction phase, wavelet filter transforms are used to distinguish between delta, theta, alpha, beta, and gamma waves. In the feature reduction phase, principal component analysis is employed for feature reduction. After obtaining the principal components, classification is done using support vector machines.
A test bench written in Xilinx 14.5 to determine the eigenvalues of a 2*2 matrix using the VHDL programming language and the CORDIC square root algorithm (coordinate rotation digital computer). VHDL code is loaded into a black box and receives the output of eigenvector computations from Simulink. Additionally, I utilised System Generator to design the hardware block.

C. Experimental Results

Table 1: Comparison of results of different algorithms.

Algorithms	Min	Max	Mean	Accuracy
Log Reg	89.93	75.88	89.11	76.13
GNB	69.415	54.72	83.13	59.70
KNN	82.15	77.88	88.99	81.99
SVM	96.98	88.19	93.52	87.30%

Based on the table above, which is the result of a comparative study of various algorithms, we have analysed different factors to compare the quality and efficiency of the algorithms. Thus, finalizing the SVM algorithm to be the best of all as it is the finest classifier.

```
In [66]: import pandas as pd
         # 1. Normalising data and getting transpose
         normalised = pd.DataFrame(normalize(data, axis = 0))

         # 2. Finding covariance matrix
         covariance_df = normalised.cov()

         # 3. Eigen Vectors
         u, s, v = np.linalg.svd(covariance_df)

         # 4. Principal Components
         data_reduced = normalised @ u
         data_reduced.head()
```

Out[66]:

	0	1	2	3	4	5	6	7	8	9	...	610	611	612	613	
0	0.214740	0.258232	0.483616	-0.335231	0.089806	0.020149	0.023959	0.011906	-0.272052	0.110583	...	-1.279366e-07	-7.846543e-08	2.304717e-08	-1.567827e-08	-6.242
1	0.158864	0.221441	0.362637	-0.311868	0.098472	0.009991	0.024592	-0.051707	-0.230946	0.110976	...	-1.553093e-07	-5.725032e-08	1.956170e-08	-1.156176e-08	8.797
2	0.153459	0.200484	0.304121	-0.306960	0.095141	0.006106	0.025656	-0.066683	-0.208815	0.095076	...	-1.335752e-07	-7.657077e-08	2.731356e-08	-1.060692e-08	-2.469
3	0.165317	0.226833	0.395299	-0.294446	0.110880	0.008447	0.045973	-0.059719	-0.242274	0.134821	...	-1.150134e-07	-3.515927e-08	1.576767e-09	-2.747783e-08	-2.909
4	0.135258	0.174816	0.288190	-0.249035	0.081413	0.006984	0.024832	-0.050386	-0.197184	0.096867	...	-1.324349e-07	-5.298214e-08	2.655804e-08	-3.295132e-08	-5.845

5 rows × 620 columns

Figure 4: Principal component analysis output

```
In [121]: #Support Vector Machine
          from sklearn.metrics import confusion_matrix
          from sklearn.metrics import accuracy_score
          from sklearn.svm import SVC
          Xtrain, Xtest, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
          classifier = SVC()
          classifier.fit(Xtrain,y_train)
          y_pred = classifier.predict(Xtest)
          cm = confusion_matrix(y_test,y_pred)
          accuracy = accuracy_score(y_test,y_pred)
          print("Support Vector Machine:")
          print("Accuracy = ", accuracy)
          print(cm)

          Support Vector Machine:
          Accuracy =  0.873015873015873
          [[16  1  2]
           [ 5 22  0]
           [ 0  0 17]]
```

Figure 5: Support Vector Machine Code and Outcome

To compute a square-root with CORDIC the number is yielded by multiplying, adding and testing.

L	2^L	y	x=	12056
		0	initial value	
7	128	0	128 x 128 > 12056	do nothing
6	64	64	64 x 64 < 12056	add 64 to $y_{initial}$ --> 64
5	32	96	$(64 + 32)^2$ < 12056	add 32 to last y --> 96
4	16	96	$(96 + 16)^2$ > 12056	do nothing
3	8	104	$(96 + 8)^2$ < 12056	add 8 to last y --> 104
2	4	108	$(104 + 4)^2$ < 12056	add 4 to last y --> 108
1	2	108	$(108 + 2)^2$ > 12056	do nothing
0	1	109	$(108 + 1)^2$ < 12056	add 1 to last y --> 109
-1	0.5	a.s.o.	and so on	and so on

Figure 6: An example of calculating the square root of the algorithm.

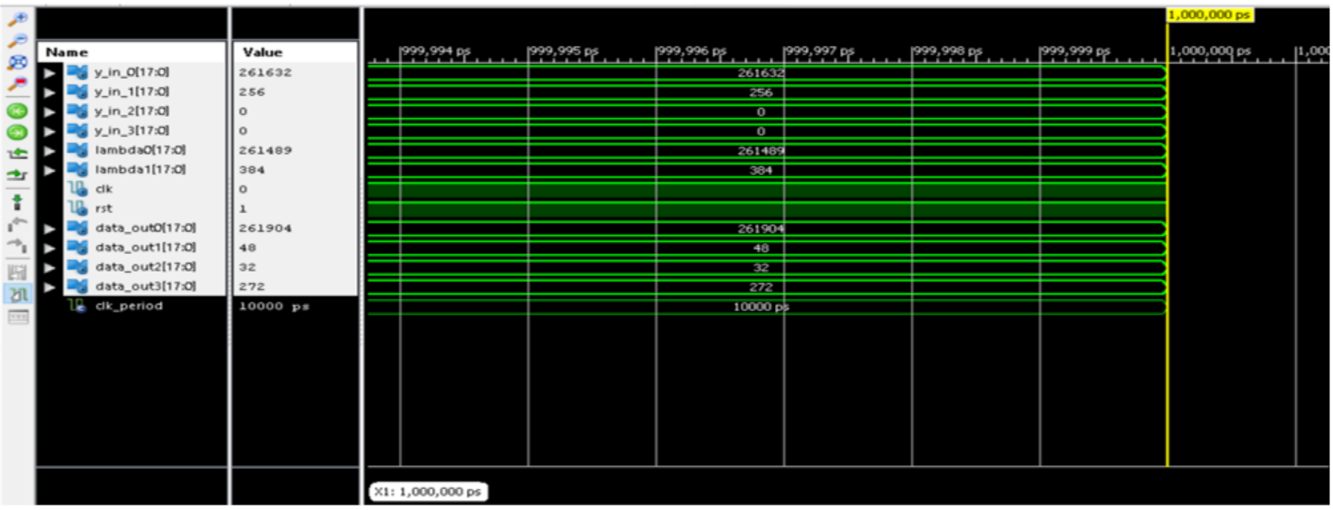

Fig 7: Simulation waveform of eigenvector calculation

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DOI: 10.35940/ijrte.B7808.0712223
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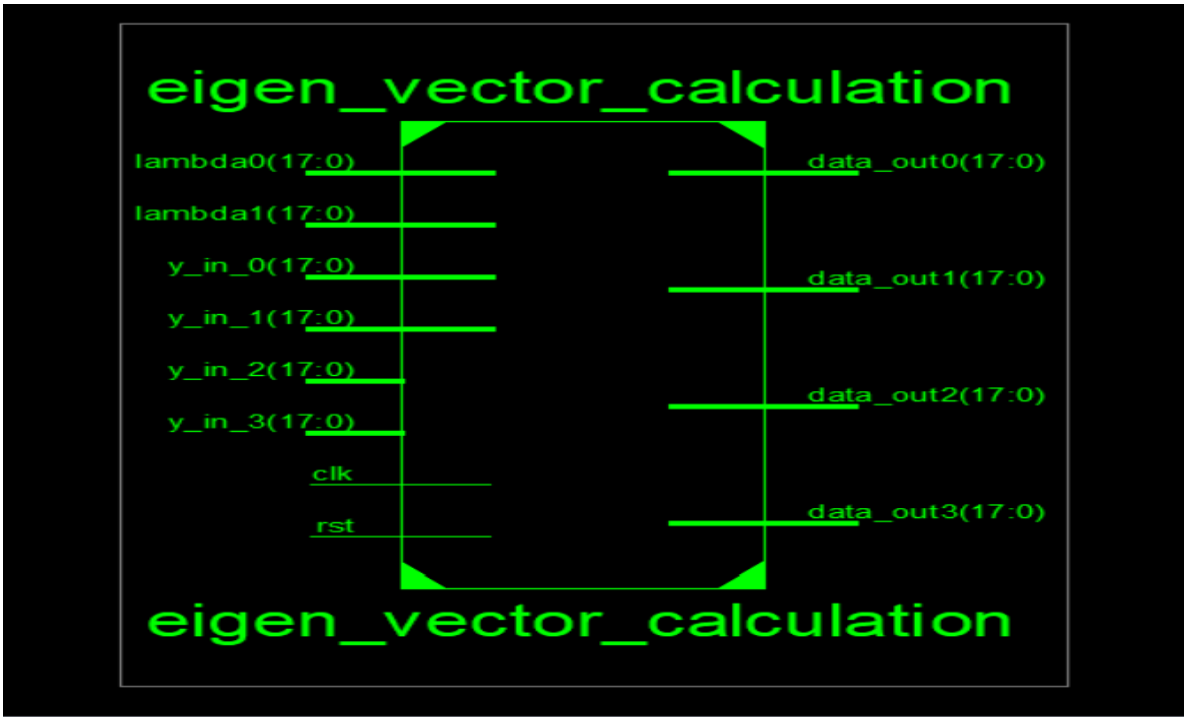

Figure 8: Schematic diagram of eigenvector calculation

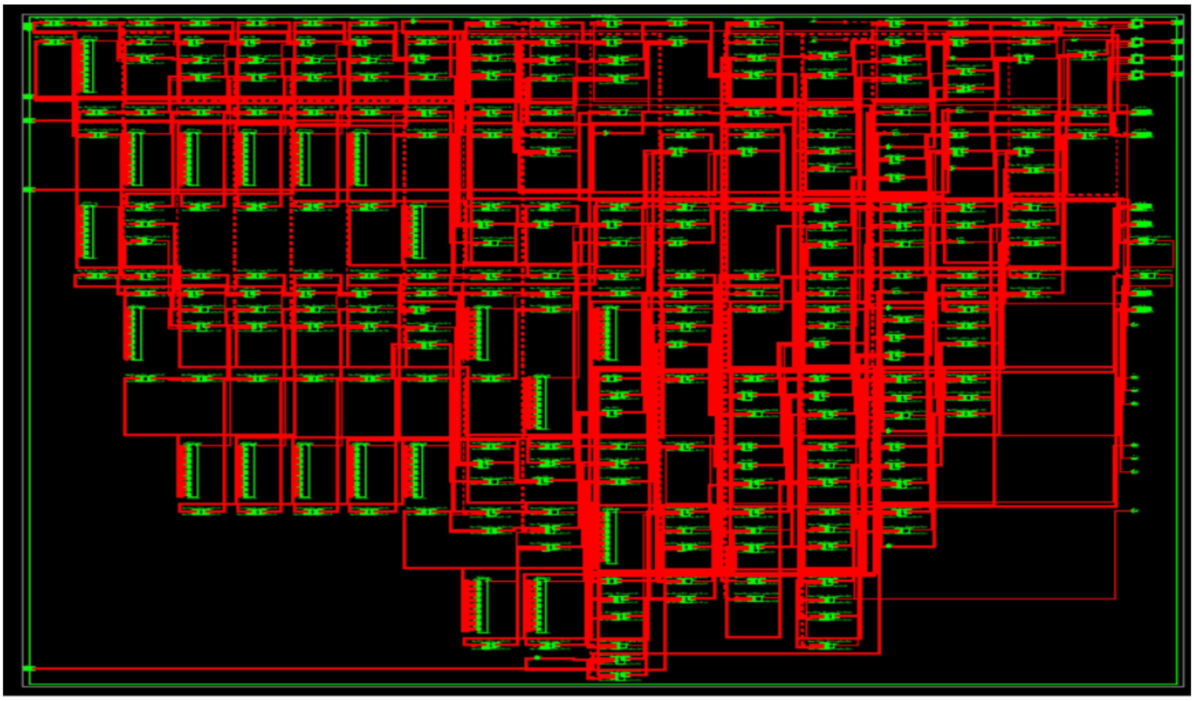

Fig 9: RTL Schematic

Table 2: Device utilization summary

Device Utilization Summary (estimated values)			
Logic Utilization	**Used**	**Available**	**Utilization**
Number of Slice LUTs	5070	27288	18%
Number of fully used LUT-FF pairs	0	5070	0%
Number of bonded IOBs	146	218	66%
Number of BUFG/BUFGCTRL/BUFHCEs	1	16	6%
Number of DSP48A1s	22	58	37%

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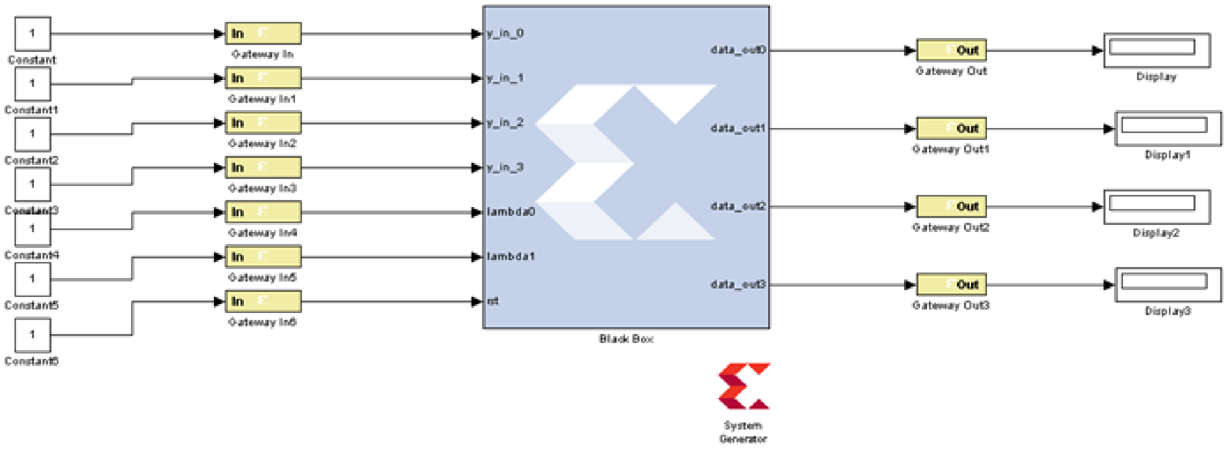
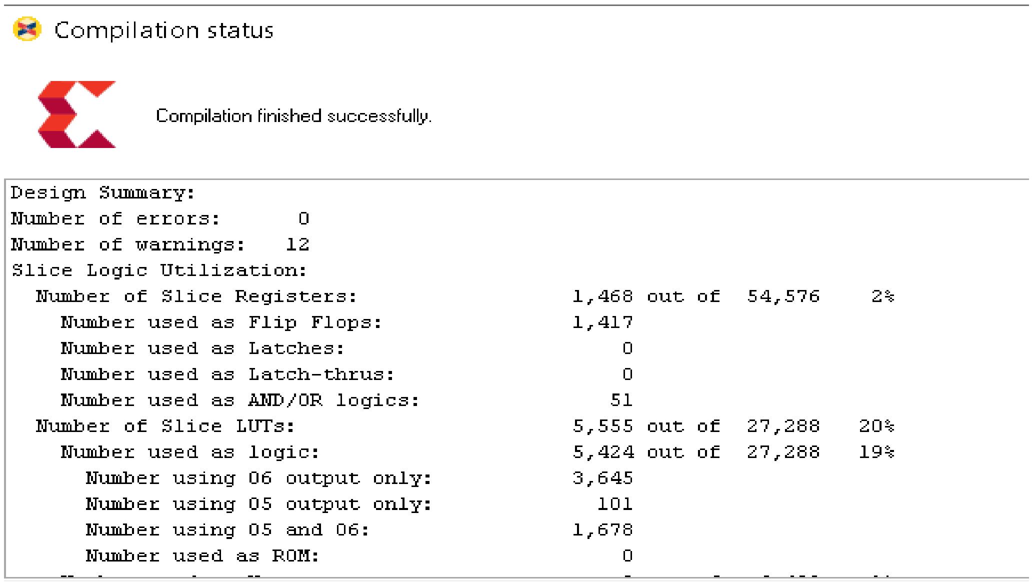


Figure 10: Simulink model for computing eigenvectors




```
Design Summary:
Number of errors:      0
Number of warnings:   12
Slice Logic Utilization:
  Number of Slice Registers:                 1,468 out of  54,576    2%
    Number used as Flip Flops:               1,417
    Number used as Latches:                      0
    Number used as Latch-thrus:                  0
    Number used as AND/OR logics:               51
  Number of Slice LUTs:                      5,555 out of  27,288   20%
    Number used as logic:                    5,424 out of  27,288   19%
      Number using O6 output only:           3,645
      Number using O5 output only:             101
      Number using O5 and O6:                1,678
      Number used as ROM:                        0
```

Figure 11: Summary of the design in the Simulink model

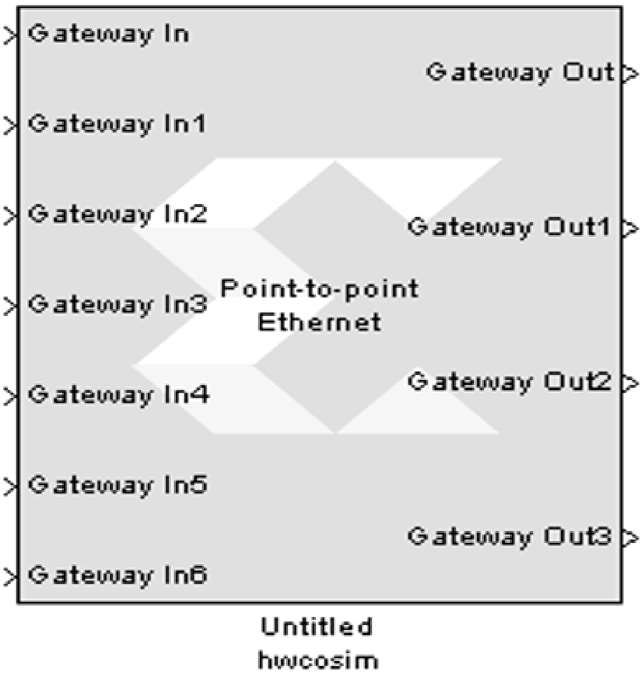


Figure 12: Simulink generates a hardware model.

V. CONCLUSION

This paper presents a new approach to recognising correct human emotions using EEG signals and the implementation of this approach on an FPGA. This approach consists of a preprocessing technique which filters the frequency range of 0 - 75Hz and sampling frequency of 200Hz. After feature extraction is completed, we obtain preprocessed EEG data, yielding 620 features. We apply PCA, Principal Component Analysis. The PCs will be fed to a Support Vector Machine Classifier to get the output. A VHDL code and test bench have been written for a 2x2 matrix and waveform. An RTL schematic has been obtained using Xilinx 14.5. Simulink model is used for FPGA implementation.

FUTURE SCOPE

Research on emotion recognition using EEG signals has been developing rapidly. Emotions are affecting every aspect of human life. The research is in its initial stages, and there is considerable room for development. Emotion recognition procedures using EEG signals have extensive applications in conjunction with signal processing and artificial intelligence.

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DOI: 10.35940/ijrte.B7808.0712223
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This processing method can be applied to a wide range of processing and AI applications. The improved PCA design can be utilised in compression and dimensionality reduction algorithms.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to our Guide, as well as the HOD-ECE and Principal of SJBIT, for supporting us in carrying out the project and publishing this article.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal contributions to this article.

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