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"An FPGA-Based Implementation of Emotion Recognition using EEG"

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CERTIFICATE

Certified that the Project report entitled **"AN FPGA-BASED IMPLEMENTATION OF EMOTION RECOGNITION USING EEG"** carried out by **Meghana M Totiger[1JB19EC052], Priyanka N[1JB19EC070], Spurthi A[1JB19EC088], Vyshnavi Shekhar B S[1JB19EC104]** is bonafide student of **SJB Institute of Technology** in partial fulfilment for the award of **"BACHELOR OF ENGINEERING"** in **2022-2023** as prescribed by **VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELAGAVI** during the academic year **2022-23**. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the departmental library. This report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said degree.

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Regards,

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Declaration

We, the undersigned, solemnly declare that the Project report entitled "An FPGA-Based Implementation of Emotion Recognition using EEG" is based on our own work carried out during the course of our study under the supervision of Mr. Darshan B D, Asst. Professor.

We assert the statements made and conclusions drawn are an outcome of our Project Phase - II work. I further certify that,

1. The work contained in the report is original and has been done by us under the general supervision of our supervisor.
2. The work has not been submitted to any other institution for any other degree/diploma/certificate in this university or any other university of India or abroad.
3. We have followed the guidelines provided by the university in writing the report.
4. Whenever we have used materials (data, theoretical analysis, and text) from other sources, we have given due credit to them in the text of the report and given their details in the references.

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ABSTRACT

An electroencephalogram is a machine that uses small metal washers or electrodes positioned on the scalp to identify all the electrical energy in the human brain. Electric impulses connect the brain cells and are active at all times and even while we are sleeping. This activity appears as wavy lines on the EEG recording. The preprocess function filters data to a frequency range of 0 to 75 Hz. It creates a new matrix with a sampling rate of 200Hz and a range of 0 to 75Hz. The Low pass filter of Finite Impulse Response was utilized. Because bandpass would make the EEG data unstable after processing. Each EEG pre-processed signal has output, completing the feature extraction. Principal Component Analysis, or PCA, is used in the feature reduction phase. PCA is a statistical process that turns around a correlated set of features into mutually uncorrelated features, or principal components, using singular value decomposition. Principal Components Analysis: (1) Mean normalization of features (2) Covariance Matrix (3) Eigen Vectors (4) Reduced features or principal components. The preceding step's PCs will be passed into the SVM classifier for emotion output. A VHDL code & test bench for a 2*2 matrix was written and the waveform, RTL schematic was obtained on Xilinx 14.5. For the FPGA implementation, the Simulink Model was designed and the eigenvalues were computed using a system generator.

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LIST OF ABBREVIATIONS

Abbreviations	Stands For
EEG	Electroencephalography
ANS	Autonomous Nervous System
PCM	Principle Component Analysis
SVM	Support Vector Machine

Chapter 1

INTRODUCTION

Throughout their lives, humans engage with many machines. Emotions, too, are essential an unavoidable in everyone's existence. Encounters between humans and machines are discrete andobvious occurrences in which the machine learns about the human only when an explicit command, such as pressing a button, is provided. The relationship between humans and machines can be described as less autonomous and intelligent. Scientists have discovered that emotional intelligence isa fundamental component of intelligence.

Scientists have demonstrated that substituting a single of its human in HHI which is known asthe Human-Human Interaction with such a machine adheres to the similar essential norms of this kind of interaction between humans.

Picard, a pioneer in the subject of Computing Effectively, asserts that "Human Emotions play a critical part in rationality, comprehending, learning, and a lot more related to other important cognitive functions." As a result, the design of the previously mentioned system would anticipate the way for many relevant, powerful, realistic, and dependable interactions between machines and humans.

Various ways have been developed to identify a person's underlying emotion. Specifically, emotional identification from an expression of the face, speech modulation, signaling, and Autonomous Nervous System also abbreviated as ANS signals such as pulse rate & Galvanic Skin Response (GSR) have been carried out.

The extraction of ER from brainwave patterns is a relatively new development in the realm of emotional evaluation. The technique of ER from EEG recordings overcomes some of the drawbacks that may arise when utilizing the approach of ER from the facial aspect, heart rate, and GSR, such as facial expressions may be readily faked, for instance, an individual may be feeling agony inside but display a pleasant expression.

Signals from the nervous system which is automated are more delicate to noise; for instance, GSR signals may come not just from emotions as input but it may also come from physiological influence.

On the adverse, signals which come from the nervous system, such as EEG, are collected from the source of experience of emotions. Furthermore, EEG signals with full resolution are inexpensive to make records. To categorize emotions from EEG signals, various methodologies and steps are required.

These processes include capturing signals, pre-processing raw data to withdraw artifacts, making extracting most behaviors that people from the signals which are processed, and preparing the dataset, accessing with ML tools.

Emotion is crucial in our daily lives and at work. Real-time emotion assessment and regulation will enhance and improve people's lives. Emotion recognition, for example, will make the human- machine interface relatively easy and more natural. Another example is that in the care of patients, particularly those with expression issues, clinicians will be able to have more proper medical care if they are aware of their patients' true emotional condition. EEG emotion identification has gained plenty of interest in current years. It is also a critical aspect of brain-computer computer interface (Brain-computer- computer interface) systems, which will significantly improve human-machine communication.

For emotion detection from EEG data, several features and extraction approaches have been presented, including time-frequency approaches, time-frequency- frequency technics, combined time-frequency analytical techniques, and other tactics.

While the human emotional state is important in daily life, the scientific aspect of human emotional responses is still quite restricted. The advancement of emotional sciences is critical to the advancement of the human mind for such advantage and applicability to society. When pieces of machinery are incorporated into the system that helps recognize these emotions, productivity and expenditures are improved in a variety of ways. For example, machine integrations into societyincluding such education can detect whether students' mental states toward the components of the educational resources are engaging or no engaging.

A psychological phenomenon is the emotion intervened by the individual's requirement in urge, consisting of consist of the following: increased heart rate, subjectivity, and performance in the outside world. The response to emotions is referred to as arousal.

While content or cheerful, the heartbeat slows down, heart-rate increases, respiration rate increases, and an intermittent or stop occurs, when painful, the volume of the blood vessel reduces. According to similar studies, women are most prone to elicit emotions than males, and the level of neurobiological reactions is greater.

Non-physiological and physiologic signals could be used to detect emotions. Images of facial gestures, vocal signs, and body gestures are examples of signals which are non-physiological & Physiological, as opposed to non-physiological signals, and can be sensed by several wearable devices, including an EEG (EEG), electromyogram, electrocardiogram, galvanic skin reaction, blood volume pressure, and photoplethysmogram. Among these physiological signs, EEG signals have been frequently used in emotion recognition studies

. Emotions could be reflected instantaneously by an EEG signal recorded from the brain by a setof EEG electrodes after a person receives the stimulations.

Subjective experience refers to an individual's feelings concerning various emotional states. Other people's reactions to the same stimuli may differ. Expressions refer to the external presentation of emotions.

1.1 THE BRAIN

The brain is still incredibly the most complicated and biggest organ in the body of humans. The brain is composed of almost 100 billion nerves. It is in charge of all bodily actions and reactions. It continually receives sensory information, processes it, and responds accordingly, directing all bodily actions and functions including sensation, appetite, thirst, sleep, body movement, and many other activities that lead to the existence of humans.

The brain is perhaps the most extensively complicated organ in the body, according to biological studies. The cortex is indeed the bulkiest region of the brain and contains a type ofelectrodermal signal, the electrical brain signal, with an amplitude of approximately 10 V 100 V. The cerebral cortex is partitioned into four sections: the frontal lobe, temporal lobe occipital lobe & parietallobe.

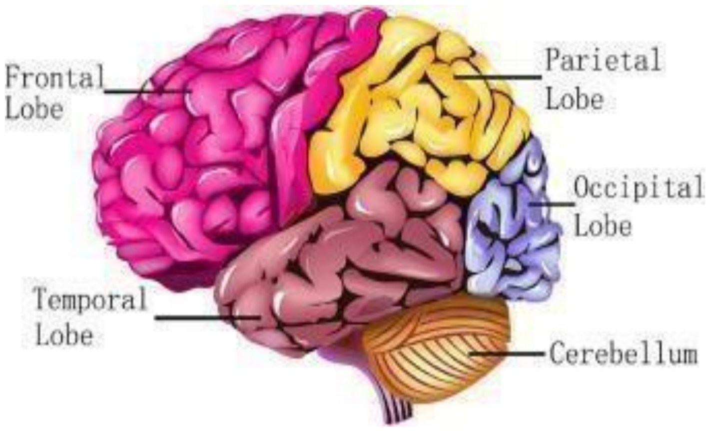

Fig 1.1 Physical structure of the cerebral cortex.

The frontal lobe's principal role is intellective reasoning and taking care of emotional needs. The right hemisphere acknowledges to human touch experience and is associated with coordination and balance in the human body. The spatial and temporal lobe is associated with emotional and psychological activity and is largely responsible for perception and scent. Finally, the visual cortex is in charge of visual information processing.

1.1.1 STRUCTURE OF THE HUMAN BRAIN

The brain is bifurcated into three layers based on function. The first portion is the massive brain, commonly known as the cerebrum.

This section is in charge of controlling functions such as speech and giving reasons. The second component is called the brain stem, which governs visual and auditory function, and the cerebellum is the third part, which controls coordination and movement.

The lobes in the brain are subdivided as follows:

- The frontal lobes are in charge of judgment, reasoning, problem-solving, and parts of speech.
- The parietal lobes are in charge of movement and handwriting.
- The temporal lobes are in charge of hearing.

1.2 ELECTROENCEPHALOGRAPHY (EEG)

Brain activity generates a variety of signals, including magnetic and electrical impulses. This action can also be documented by making use of a variety of methods, which are often classed as invasive or non-invasive. In an invasive procedure, intervention is surgical & is used to implant a device in the brain, whereas non-invasive methods do not use such intervention.

Among the various non-invasive technologies for recording brain waves, EEG signal is among the most regularly utilized. EEG is recognized as a non-invasive method for recording brain electrical activity, which would be depicted as fluctuation of the voltage caused by current flow within the brain's neurons. Electrodes are placed on the scalp so, over brain record EEG waves, straight forward can be expressed as a signal over time.

1.21 TYPES OF SIGNALS IN THE BRAIN

The EEG is a time-dependent voltage measurement. EEG characteristics are significantly reliant on the level of cerebral cortical activity. In general, EEG signals represent a collection of waveforms and are categorized based on

1) Frequency
2) Magnitude
3) Morphology of waves
4) Geographical distribution
5) Reactivity

One of the most frequent categorizations employs the frequency band of the EEG waveform, which allows EEG signals to be divided into five distinct frequency bands.

As a result, the five distinct frequency bands, as well as the mental states connected with them, are briefly discussed below.

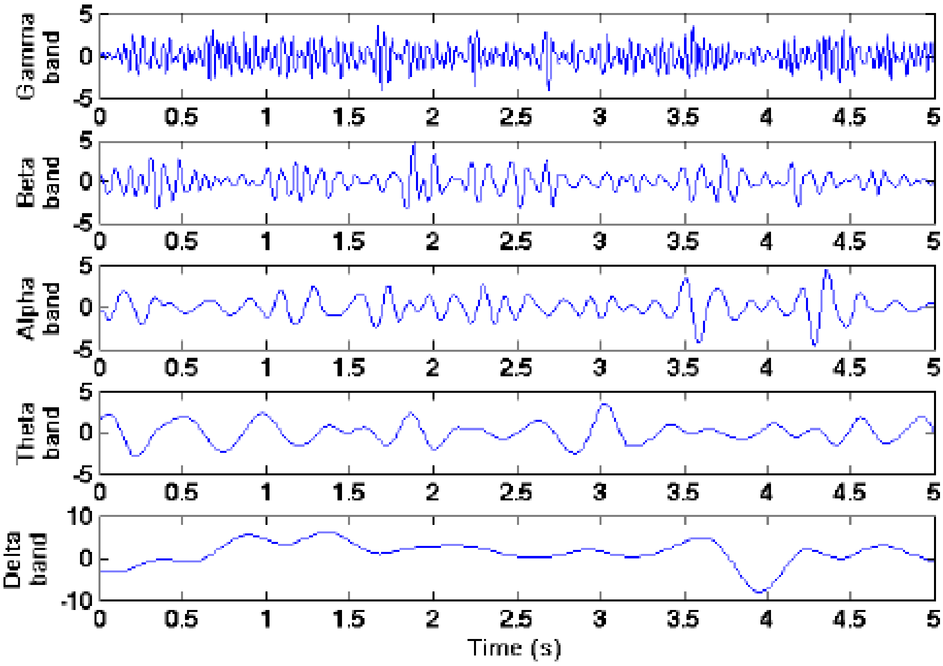

Fig 1.2 Different frequency bands in EEG signals.

Delta: a wavelength of 3 Hz or less. It has the most significant amplitude and moves the slowest. It is usual as the main rhythm in babies up to one-year-old-year-old, as well as in sleep phases 3 and 4. It might manifest as isolated subcortical lesions or as widespread lesions, metabolic encephalopathy, edema, or deep midline lesions. In adults, it is typically most visible in the front.

Theta: does have a frequency range of 3.5 to 7.5 Hz and therefore is considered a "slow" activity.It is natural in youngsters under the age of 13 and while sleeping, but abnormal in conscious adults. It can appear as a sign of localized specific brain lesions; it can also appear in a broad distribution in diffuse illnesses such as metabolism encephalopathy or some cases of hydrocephalus.

Alpha: It does have a frequency range of 7.5 to 13 Hz. Is typically found in the posterior portionsof the skull on either side, with the dominant side having a greater amplitude. It appears when you close your eyes and rest, and it disappears when you open your eyes or are alerted by any method (thinking, calculating). It is the predominant rhythm observed in typical, relaxed people. It is present for the majority of one's life, especially just after the thirteenth year.

Beta activity is defined as "quick." It also has a frequency of 14 Hz or higher. It is most visible frontally and is frequently observed on both sides in a symmetrical distribution. Sedative-hypnotic medicines, particularly benzodiazepines and barbiturates, amplify it. In regions of cortical injury, itmay be nonexistent or diminished. It is widely accepted as a natural beat. When patients are attentive, anxious, or even have their eyes open, this is the prevailing rhythm.

The distinct frequency bands of EEG signals are associated with conscious human actions. Delta waves are frequently observed during the unconscious stage of deep, peaceful sleep. Theta waves are related to sub consciousness and appear during sleep, dreaming, and drowsiness. Theta wave on the prefrontal midline increase when favorable emotions are generated.

Whenever a person is calm but cognizant, alpha waves appear. The imbalance of alpha waves and alpha waves inside the forebrain represents the emotional valence, and the midline longitudinal channel is critical in the investigation of EEG data. Alpha waves have more rhythmic energy when compared to beta and γ waves in negative and positive emotions.

Whenever the human brain is busy and focused, beta waves occur. The presence of higher beta waves inside the forebrain can imply emotional valence which is the extent to which the negative and positive emotions are classified. The average output ratio of alpha and beta waves can indicate that the state of the brain is busy. Gamma waves are related to increased brain activity. Studies have demonstrated that using the gamma, beta & alpha waves simultaneously for emotion identification is more accurate.

EEG signal-based emotion recognition study demonstrates that EEG data have immotile features in emotions. Furthermore, the valence of the emotion is asymmetrical in the frontal area, and alertness is linked to the activity of the area of the forehead. Emotion EEG is much more completely elicited in the reduced band rather than in the elevated band as well as the negative feelings are more wholesale and enormous than happy emotions.

With the presence of frightening, sad, joyful emotions, the mean strength of the Theta waves, beta waves, and alpha waves in the middle of the brain would be remarkably dissimilar, whichdesignates that the power spectrum in the midline of the EEG is the most useful aspects of emotion categorization.

P. Li et al. used a connection network that was functional in conjunction with local activation to show how brain areas which respond to emotions and reflect interactions between important brain areas. Some of these investigations highlight the association in the middle of emotional symptoms and the properties of the related EEG signals, which is more useful for investigating the classification of signal emotion in EEG.

The Signal acquisition technology and the distribution of electrodes play selection critical roles in emotion extracting features, analyzing, and categorization during the EEG data acquisition process. The collecting equipment and electrodes are routinely utilized in various emotional EEG research.

There are two methods for collecting EEG signals: invasive and non-invasive. The intrusive approach provides a signal-to-noise or SNR ratio that is high with the intensity of the signal Yet, itmust be inserted inside the cranial cavity via the surgical method, and the electrode penetrates the center of the brain, making it difficult to operate. Attempting to contact the acquisition electrodes on the participant's scalp is a non-invasive, easy acquisition method that is widely used in modern brain- computer interface research.

Referring to Fig. 1.3, emotion-related EEG electrodes were found to be mostly dispersed in the temporal lobe margin, posterior occipital lobe, and prefrontal lobe. These areas corresponded exactlyto the physiological mechanism of emotion detection. By changing the electrode distribution, the recovered data dimensionality can be significantly decreased. The intricacy of the computation can be simplified, making the trail

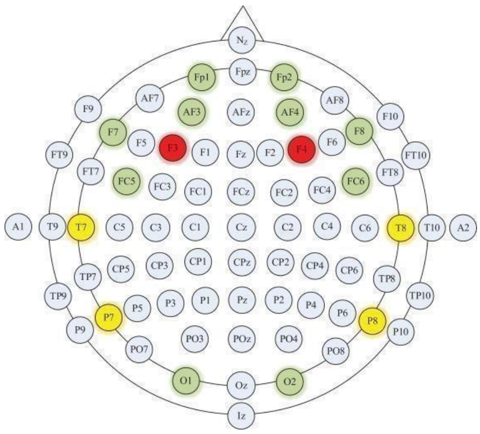

Fig 1.3 Lead system with 10-10 standard electrodes

1.3 OBJECTIVES

- To identify human emotion.
- To lessen the data dimensionality as well as to make improvements to the classification results.
- To improve the accuracy using a support vector machine.
- To implement emotion recognition on an FPGA.

1.4 CHALLENGES AND MOTIVATION

- Emotion Recognitions solutions require a lot of data to be trained.
- Incorrect emotion indicators.

Chapter 2

LITERATURE SURVEY

The suggested algorithm's goal is to recognize facial expressions in digital photographs. To recognize facial expressions, particular and predetermined aspects of the image must be extracted. For example, 21 locations on the human face can be recognized as changing as a function ofemotional states. Facial expressions can also be recognized by monitoring these feature points.

The neural network which is multilayer being used to group face expressions in many articles. Furthermore, edge detection is employed to locate and dismantle facial components. Following the development of a method that is accurate, it is simulated using Matlab software for an FPGA board by hardware description language VHDL.

Facial image captures were processed priorly in several phases, which involves binary image transformation and noise removal. The photos were then subjected to feature extraction, with eight features chosen. After that, a neural network with 8 neurons in each layer, 7 cells in the hidden units, and 6 cells in the output nodes was created.

The JAFFE dataset was used to test and verify the results. Using various simulations, we discovered that the suggested algorithm's average accuracies for facial expression identification in MATLAB and Quartus are 91.76 percent and 86.67 percent, respectively. [1]

Many studies have recently been undertaken on the identification of facial expression using convolution neural networks also abbreviated as CNN, which perform exceptionally well in computing machines. The CNN design which has many parameters and the highest computational complexity is necessary to achieve good classification accuracy.

Unfortunately, this cannot be termed as appropriate for embedded devices with low hardware resources. We describe a compact architecture of CNN suitable for embedded systems in this study. The suggested CNN architecture has low computational complexity and a small memory footprint.

In addition, a unique device quantization method based solely on arithmetic integers is initiated. The suggested hardware beneficial quantization approach maps scaling variables to terms of power- of-two and substitutes division with shift and factor multiplication for operations.

We created the FERPlus-A dataset to improve the general performance of the classifier of the CNN. The training dataset was created by combining many image processing methods. Quantization was conducted after tutoring with FERPlus-A.

A quantization CNN variable is around 0.39 MB in size and has approximately 28Minteger operations (IOPs). The classification accuracy of the quantization CNN that uses solely arithmetic integers on the FERPlus testing data is around 86.58 percent. In previous studies, it outperformed other lighter CNNs in terms of accuracy. The suggested architecture of CNN which uses only arithmetic integers is executed for facial emotion identification is real-time on the Xilinx ZC706 SoC framework using parallelism methods and effective data caching strategies. The FPGA-based CNN processor used for real-time facial expression identification produces roughly 10 FPS at 250 MHzand uses 2.3 W. [2]

This research proposes electroencephalography also abbreviated as EEG which is based real- time emotion detection architecture of hardware system for binary and quaternary segmentation based on multiphase deep convolution network principles to achieve on a technology chip of 28-nm and field-programmable gate array also abbreviated as FPGA. For emotion feature extraction, sample entropy, differential asymmetries, the brief Transform, and a channel reconstructing method were applied. The six EEG channels (FP1, FP2, F3, F4, F7, and F8) were chosen for this study, and EEG images were created using spectrogram fusions.

We presented the execution of a multiphase CNN strategy to handle constraints in the hardware resource in the whole architecture of CNN, which includes the training and acceleration for effective artificial intelligence applications. The proposed architecture was validated using the DEAP database with 32 subjects, with average levels of accuracy for binary valence categorization and quaternary valance–arousal categorization of 83.36 percent and 76.67 percent, respectively.

The area and total consumption of was CNN chip's core consumption were 1.83 x 1.83 mm2 and 76.61 mW, respectively. The microchip functioning was tested using ADVANTEST V93000 PS1600, as well as the trained and real-time classifying clarification times for each EEG image were 0.12495 ms and 0.02634 ms, respectively.

The suggested real-time EEG-based emotion detection system includes a dried electrode EEG headpiece, extraction of features processors, CNN chip platforms, and graphical connection point, with each emotional situation recognition taking 450 ms to complete. [3]

Emotion recognition aids in the monitoring and comprehension of human emotional states, which is important in immediate and potential intelligent machines. Speech emotion detection is the ability to detect human feelings and emotional states through speech. Neutrality, joy, and sadness are one of the feelings considered for the trials.

An individual's emotions are mostly determined by bodily qualities such as muscle stiffness, skin elasticity, hypertension, heart rate, breath, speech, and so on. A person's emotions are unique,yet their interpretation, interpretation, and responses can be distinct. Python libraries are used for this analysis. [4]

Emotion recognition has been a popular study topic changing along with any advancement of machine learning in computing machines. In this paper, we present a Gate Array also called the FPGA Array or FPGA architecture for this assignment that employs a lonely approach known as a convolutional neural network also known as CNN. The emotion identification structure detects faces in a stream of videos using the camera of VITA-2000 setup and processes the picture data with the tutoring model of CNN.

The design is built around the Zynq-7000 All Customizable Videos of SoC and Imagery Kit. As the network has been trained, the weight from the Tensorflow models will be converted into C- arrays for usage in Vivado HLS. Any number of Weights can be implemented in an FPGA system after they have been converted to C arrays. We can also fully test the CNN's functioning by generating the design with a C++ compiler. The posed-emotion dataset was used to teach this technique (FER2013). The outcomes which reveal that with greater finer tuning and complexity, the Cnn architecture outperforms emotion recognition algorithms as a state of art. They also put forward some novel conceptualizations for broadening the concept of sliding windows and visual key features [5]

The disease is a progressive neurodegenerative illness characterized by a series of abrupt seizures caused by temporary and recurring electric discharge in the brain. Electroencephalogram (EEG) signals can be used to detect them. Because of the significant information, it contains regarding brain processes, EEG is the most often utilized clinical test for neurological illnesses. The work reported in this article is divided into two sections. The first section describes and validates our detection method using the AntMiner+ classification algorithm. The second section is about designing and implementing our applications on the Xilinx ZC702 integrated board. [6]

Passenger security in public transit, particularly in shared cabs and taxis, is frequently overlooked, and few preventive measures are implemented. Emotion identification from facial gestures is a possibility in the connected mobility future, but a faster processor and edge machine to extract anomalous state conclusions will be more appropriate for any further alerting about the passenger's safety.

FPGA design is a suitable option that is not only implemented in embedded systems for automotive electronics, it can also be used for quick inference outcomes, hence making it a perfect real-time contender for customer anomalous state identification. A real-time emotion recognition system based on face features was constructed using FPGA for the same purpose.

A Binary Neural network also abbreviated as BNN which is fed by a Local Binary Pattern (LBP) outcome was created to create a better and speedy face recognition system. LBP is set up in a processing phase to extract facial components, which are then fed to the BNN layer for appropriate inference.

The Viola-Jones (VJ) technique is used in the preprocessing approach to identify facial information while removing extraneous information from images. The LBP-BNN network is trained using the Face Interpretation 2013 (FER-2013) data set. For inference, the specialized hardware accelerator or overlay is synthesizable, as well as the intended IP is executed on FPGA. To achieve faster-categorized results, the inference is performed on FPGA using the training model. Emotion recognition by facial expressions is divided into six categories: joyful, sad, surprised, angry, disgusted, and fearful.

The network of LBP-BNN is a built-in FPGA to achieve facial emotion which is real-time identification by taking a person's image from a webcam interface to communicate to the FPGA functioning as a cloud device with acceptable accuracy with the inference device The makingemotion detection approach is well-suited for additional implementations, such as emotion tracking for patients with mobility disorders in hospitals. [7]

Recognition system became one of the most important factors to address in any Affective Computing project. Several studies in emotion recognition have found that Artificial Neural Network is an efficient approach with a state-of-the-art that achieves recognition performance recognition. There are numerous approaches for using the CNN model and doing experiments in software. In traditional software-based computation, on the other hand, the demands of real-time picture processing are not quick enough to fulfill. As a result, we offer a systematic FPGA-based technique for expression recognition. This model is used to characterize seven basic categories of human emotions: irritated, fearful, disgusted, pleased, sad, and neutral, by extracting features from those layers. The model evaluated functionality on FPGA simulations and attained over 85%.[8]

Using traditional backpropagation and gradient descent, we offer a method for training quantized thresholds (TQT) for uniformly symmetric quantizers. In contrast to previous work, we demonstrate that a careful examination of the straight-through estimation for thresholds gradient provides for a logical range-precision trade-off that leads to improved optima.

To allow for hardware implementations, our quantizers must use energy scale factors and per- tensor scale of weights and activations. We give analytical support for our approaches' general resilience and empirically evaluate them on ImageNet classification CNNs. With much less than Five epochs of quantization (8-bit) retraining, we can attain near-floating-point accuracy on previously tough networks such as Mobile Nets. Finally, we introduce Graffitist, a framework for the automatic quantization of images. for automatically quantizing TensorFlow graphs for TQT. [9]

Image-based emotion recognition is an important topic, particularly for understanding human feelings or emotions in certain situations, such whilst also going to the movies or playing a computer game. Furthermore, one of the key technologies which have been proved to be suitable for the projectof image-based facial image detection is the type of neural network (CNN). As a result, the available CNN architecture enabling image-based emotion recognition concentrates on efficiency instead of other variables such as parameter set and execution time. We investigated whether transferring knowledge from a moderate and big dataset may boost the effectiveness of a compact Cnn model on an image-based facial emotion identification task.

They investigate the impact of transfer learning on five unique datasets, namely CASIA- WebFace, CASIA-WebFace, CASIA-WebFace, CIFAR10, CIFAR100, ImageNet32, CINC-10, and, utilizing a lightweight residual-based CNN architecture designed originally for the CIFAR dataset. The FER+ (Facial Emotion Recognition +) database is used to assess the performance of the lightweight CNN architecture. Experiments show that even when using transfer learning on a medium-sized dataset rather than training the model from scratch, our condensed CNN classifier can be improved. [10]

In this paper, we offer many enhancements to any recognition of facial expression (FER) system's performance. We assume that variations in the placements of the reference points and intensities capture critical information about a facial image's mood. Researchers propose using a deeplearning model to incorporate the gradients and Wavelet transform of both the image pixels and the original input (CNN). These changes assist the network in learning extra details from the gradients and Wavelet transform of the images. However, a simple CNN cannot retrieve this information from raw photos. We ran several trials on two well-known datasets, KDEF and FERplus. Our method improves on the already excellent performance of cutting-edge FER. systems by 3 to 5%.[11]

Automated recognition of facial emotions in the wild is a difficult topic that has piqued the interest of computational image analysis and pattern recognition communities. Deep learning approaches have demonstrated their effectiveness in expression recognition (FER) problems since their inception. However, because these methods are parameter intensive, they cannot be used in real-world applications on resource-constrained embedded devices. To address the constraints of deep learning-inspired FER systems, we describe in this research an effective dual integration convolutional neural network (CNN (CNN) model for real-time facial expression recognition on an embedded device.

The designed DICNN model outperforms optimal results by maintaining a proper balance between identification performance and computational efficiency with only 1.08M variables and 5.40 MB ram storage space. The CNN model was assessed on four FER benchmark problems (FER2013, FERPlus, RAF-DB, and CKPlus) utilizing several performance evaluation criteria, including recognition rate, precision, recall, and F1-score. Finally, we improved the intended DICNN model using TensorRT SDK and implemented it on an Nvidia Xavier embedded system to provide a compact system with high throughput inference. Comparison results of the analysis with other state- of-the-art approaches indicated the efficiency of the developed FER system, which attained a reasonable degree of certainty while improving execution time by a factor of ten. [12]

In general, facial expressions can be divided into two types: static expressions and micro expressions. Facial expression recognition has numerous intriguing uses, including pain detection, deception detection, and babysitting. When used to recognize micro-expressions, standard convolutional neural (CNN)-based approaches have two major flaws. For starters, they are typically reliant on extremely deep models that overfit little datasets. Nonetheless, reliable interpretations are tough to obtain, and meaningful datasets are often small. Second, whenever it comes conto considering micro-expressions, these methods usually ignore the parametric statistical properties of micro-expressions, which might be leveraged to reduce temporal complexity.

In this paper, we introduce a thinner CNN (SHCNN) model with only three layers for categorizing static sentences and micro-expressions simultaneously without extensive training datasets. We improve the existing saliency maps by including a shrinkage factor to further clarify the functioning of our SHCNN design after analyzing the performance degradation of existent saliency CASME, SAMM, FER2013, FERPlus, CASME II, and are the datasets used in the experiments.

Towards the author’s knowledge, when compared to alternative methods that supply source code (or pseudo-code), we believe our technique would have achieved the best performance on CASE, FERPlus, and CCASEII and would have been competitive on FER2013 and SAMM. [13]

Emotion recognition algorithms that are effective can help machines comprehend people and facilitate the evolution of human interaction applications. Many research initiatives in recent years have employed baseline expressions data to train deeper CNN architectures to produce cutting-edge outcomes. These high-accuracy models typically have hundreds of layers, necessitating complex calculations and making them unsuitable for real-world applications. To address the latency issue under natural situations, this research develops a lighter-weight emotional expressions (LER) model. [14]

The following are the three main contributions of this study. 1) In a framework that eliminates superfluous parameters, the LER model includes a tightly coupled convolution layer along with model compression methodologies. 2) In our work, we preprocess visual information using multichannel input, which enhances the model's learning capacity. 3) On the FER2013 and FERPLUS datasets, experimental results show that the LER model outperforms alternative lightweight models. When compared to previous studies, the LER model improves precision & reduces the number of factors by 97 times. Lastly, the FERFIN database was developed, which has fewer noise data and more exact labeling than the FERPLUS dataset. [15]

Recent machine learning approaches employ progressively vast convolutional neural networks to deliver cutting-edge results in a variety of domains. The increased performance comes at the expense of a significant increase in calculation and storage requirements. This makes the real implementations on hardware with limited resources difficult. One popular technique for addressing this difficulty is to use neural network quantization to do low-bit precision computations. However, aggressive quantization usually comes at a considerable cost in terms of accuracy, necessitating network retraining or turning to greater bit precision quantization.

We formalize the linear quantization challenge as a Minimum Mean Square Error (MMSE) issue for both weighting and authorizations in this research, enabling low detection inference without the requirement for extensive network retraining. We suggest analyzing and optimizing limited MSE problems for hardware quantization. The suggested method enables 4-bit integer (INT4) quantization for pretrained model deployment on restricted hardware resources. Several studies on various network designs show that the proposed strategy produces cutting-edge outcomes with minimum loss of job accuracy. [16]

Quantization is a useful approach for decreasing neural network interpretation memory and time However, for retraining during quantization, most existing quantization algorithms requireaccess to the original training dataset. This is frequently not allowed for apps that include confidential or sensitive data, for example, owing to privacy and security concerns. Existing zero-shot quantization approaches handle this with various algorithms, but the results are poor, especially when quantizing to extremely low precision. To overcome this, we present ZEROQ, a revolutionary zero-shoot quantization framework. ZEROQ allows for mixed-precision quantization without requiring an approach to tutoring or validation data. This can be accomplished by optimally using it for a Refined Dataset, which is designed to suit the characteristics of regularizing across various network levels. Both regular and mixed-precision quantization are supported by ZEROQ. For the latter, we present a new Pareto frontier-based way of determining the made by mixing bit configuration for all layers automatically, with no search engine required. On ImageNet, we exhaustively test the proposed technique on ResNet18/50/152 and InceptionV3, and also RetinaNet- ResNet50 on the. Ms. COCO database.

More specifically, we demonstrate that ZEROQ outperforms the previously proposed DFQ [32] approach on MobileNetV2 by 1.71 percent. Furthermore, ZEROQ has a very low computing overhead and can complete the full quantization operation in under 30 seconds (0.5 percent of thetime taken for one epoch training We have developed the ZEROQ framework1 [17].

Deep networks may be computed and stored in memory more efficiently when their bit-widths and weights are reduced, which can be critical with their deploys to devices that are resource-limited like cell phones. Nevertheless, lowering quantization with bit widths often results in significantly reduced accuracy. To address this issue, we propose using an easy-to-traumatizer that modifies and discretizes activations and weights to learn to quantize them.

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We specifically approximate the quantization frequencies and find their best values by directly decreasing the network's loss to the task. This quantization-interval-learning (QIL) technique allows networks that are quantized to preserve the accuracy of full precision (32-bit) networks with bit widths as 4-bit lower and to prevent precision deterioration as bit widths are reduced which be 3 and

2-bit. Furthermore, because the quantizer can be trained on a diverse dataset, it can be used to quantize pre-trained networks for the training examples without access. We show how our trainable quantizer beats existing methods to attain state-of-the-art accuracy on ImageNet datasets using various network topologies such as AlexNet, -34 & ResNet-18. [18]

Deep networks that conduct average accuracy computations at inference time provide a power& space advantage over high accuracy alternatives, but they must solve the difficulty of retaining highly accurate as precision falls. We present Learned Step Size Classification, a method for having trained such networks that achieves high accurateness to date on the Imagenet database when using models with weight training and authorizations quantized to 2-, 3-, or 4-bits of exactness, and it can train 3-bit models that achieve full highly precise baseline accuracy.

This method improves on existing approaches for training values in quantized networking by optimizing the configuration of the quantizer itself. We present a novel method for estimating and scaling the task losing gradient at each weighted and activation layer quantizer step size, allowing itto be learned alongside other network parameters. This method employs various degrees of precision as required for a specific system that needs only a minor update to the existing training code. [19]

A convolutional neural network also called CNN has been extensively employed in categorization tasks, natural language processing, face detection, and document analysis in recentyears as an essential feed-forward neural net which that is used in the deep learning field. CNN has alot of data and a lot of multiplies and accumulates (MAC) processes. The kernel sizes and channelsizes of CNN are variable due to the diversity of application files, while the platform of the existingdevice usually employs average optimal technology, resulting in the waste of computational supplies. A novel programmable convolution computation array is proposed in this article, which has Fifteen convolution modules, each PE contains 66 operations of MAC, and it can also be customizedto compute three alternative kernel sizes of 55, 33, and 11. Simultaneously, pipeline construction is employed to synchronize convolution and pooling processes, reducing intermediate result storage.

We create a unique hardware framework to optimize the Deep ID network. The max efficiencyof each convolutional at mhz is 27 GOPS, as well as the mean usage of the MAC, is 92 percent when tested on an Altera Cyclone V FPGA. [20]

Convolutional Neural Networks also known as CNN, a common model in deep learning, have been comprehensively employed to handle a wide range of complicated issues. However, the computationally and memory-intensive layers of convolutional and layers which are fully connected limit CNN execution on embedded devices. We introduced an FPGA-based acceleration for face extracting features in this research, which facilitates the acceleration of full CNNs. Instead of using a high-level synthesizing (HLS) tool, we tune and deploy all of the CNN layers independently and separately using Verilog templates that are hand-coded. To achieve high resource usage, layers of RTL designs can adopt the nominally efficient parallelism method for the pipeline and convolution layer design for the convolutional and layer of pooling. The packet strategy is used to decrease the number of connections for the fully linked layer. As a consequence, an "ARM+FPGA" system is used to accomplish any of the hardware support of CNN, with an accuracy error of 1% less when contrasted to software [21].

This paper offers a recognition techniques (FER) system built on an SoC FPGA chip in this study. Our technology can function autonomously and automatically classify seven different sorts of fundamental emotions. We created an FPGA processing engine capable of calculating the convolution of deep neural networks and created an ideal CNN with designed hardware for such a job of emotion recognition, attaining 66 percent accuracy in the FER2013 dataset. The entire hardware system is built on an SoC FPGA that can compute up to 15 picture frames a second at a rateof 130 MHz. [22]

Automatic facial expression detection is a crucial component of an efficient human-computer interaction system, and it has been a very active study subject in recent decades. To address the challenge of facial expression recognition, numerous methods have been presented in the literature (FER). In general, present FER methods are portioned into two groups: classical machine training approaches and deep tutoring approaches.

Unlike other surveys, we hope to highlight not only the commonalities and differences of the two methods discussed below but as well as the recent phenomenon of ensemble and hybrid teaching methods in systems having FER and also providing a basic outline for each type and review of the – ability that can also be used in its constituents. On commonly used datasets, we undertake more detailed and specific competing evaluations and experimental assessments of researchers from 2014to 2020. The poll is then expanded to include our existing application situations in Vietnam. [23]

The intrinsic connections between a videotaped emotional tag and a few of its contents, and a person's impulsive responses while watching the videotape may also be used to enhance the videotape emotions label, however, many of such interlinks have yet to be fully utilized. During this research, it is present that a novel video that can be content-based has an emotional tagging perspective that is supplemented by customers' diverse neurobiological reactions that are at most needed during tutoring. A finer emotional tagging model is built by imposing commonality limitations on classifiers based on videotape content and several neurobiological markers accessible during tutoring.

Decision boundary classifiers should be used, and the proposed model's efficient learningtechniques can also be constructed. Additionally, the suggested videotape method of tagging the emotions is expanded to use insufficient physiological information, which is frequently affected by artifacts. Analyses of four conventional databases show that the method which is proposed is successful in implicitly integrating various physiological reactions and outperforming existing methods that use both full and defective multiple physiological signals. [24]

In this study, we construct and construct a multi-modal physiologic emotion database to investigate human emotions. This database captures four modal physiological data, including electroencephalography (EEG), galvanic skin reaction, breathing, and EKG (ECG). We deliberately collect a comprehensive emotion elicitation resource database selected from over 1500 video clips to mitigate the impact of culture-dependent dependent elicitation materials and generate desired human feelings. We carefully select 28 videos as standardized data extraction samples, which are examined using psychological procedures, using a significant degree of stringent man-made labeling. [25].

Chapter 3

EMOTION RECOGNITION USING EEG SIGNALS

This chapter describes the approach and software utilized. Python is the programming language used here. The block diagram has an input, which in this case is the seed dataset. The seed data set is made up of 45 Matlab files, each with 10 features and 62 channels. The input data is then preprocessed to remove any noise and to make the input data easier to classify.

In the feature extraction phase, the gamma, theta, beta, delta, and alpha waves are separated using the wavelet filter bank technique, and in the feature reduction phase, the matrix is taken and the covariance of the matrix is calculated, as well as the eigenvalues and thus the eigenvectors. The highest eigenvalue is referred to as the principal component.

After obtaining the principal component, the data is then sent to the SVM for classification. The Software methodology block diagram is depicted in Figure 3.1.

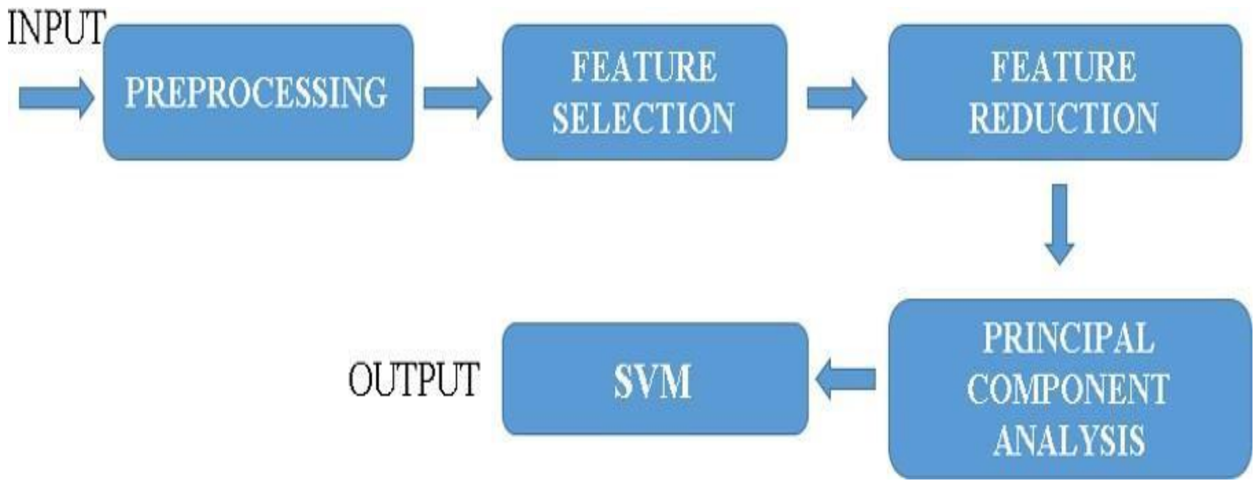


Fig.3.1 Software Methodology

3.1 PREPROCESSING

The preprocessing of EEG signals in consideration of signal purification and enhancement. EEG data is fragile and effortlessly polluted by noise from inside and outside the body. As a result, these steps are critical for avoiding contamination of the noise, which could impact posterior categorization.

The human body can generate electric signals through blink, eye, or muscle movement and also the heartbeats, which could combine with EEG signals and cause the contamination of noise.

These signals must be correctly evaluated if these artifacts need to be deleted because they may include appropriate emotional situation information which may improve the performance of emotion recognition systems. If the filters are employed, they must be used with awareness to avoid data distortions.

Filters are Low-frequency and high-frequency filters which are also referred high- and low filtersby electrical engineers, and notch filters are the three most regularly employed filter types in EEG. Thevery first two filters screen frequencies ranging from 1 to 50-60 Hz. Filters inch as Chebyshev, Butterworth, and inverse Chebyshev are chosen for EEG signal processing. Each of them seems to have unique characteristics that must be investigated.

The Filter bank has a straight performance concerning the passband & stopband but with a wide-ranging transition zone. The Chebyshev filter features a ripple with the passband as well as a transition that is steeper on the stopband, hence it is monotonic.

Another goal of preprocessing is to remove noise that could be caused by low-frequency signals which are released by a power cable interference that is an external entity, such as. Notch filters are being employed to prevent the transmission of the atheistic frequency instead of a range of frequencies. These filters are intended to get rid of frequencies generated from electrical networks, soit normally has a range from 50 to 60 Hz, which depends on the frequency of the electric signals in the individual country.

Every one of these filters is suitable for removing artifacts from EEG readings. Nevertheless, as stated previously, when utilizing filters, caution must be exercised. Filters can affect the waveform and structure of an EEG signal in the time domain. To prevent loss in EEG signal information, filtering should indeed be kept to a minimum. Nonetheless, preprocessing aids in the separation of various signals and sources.

The 'preprocess' function filters data to a frequency range of 0 to 75 Hertz. It returns an array matrix with a sampling frequency of 200Hz and a frequency range of 0 to 75Hz. We employed a 'Low pass filter' with Finite Impulse Response. Bandpass was avoided since it would cause the EEG data to become unstable after processing the 5th filter order or the filter of order 10 is used.

3.2 FEATURE EXTRACTION

During the feature extraction stage, we use wavelet filter banks to separate the electroencephalographic pre-processed input into 5 frequency sub-bands. We employ wavelet transform's filter banks to distinguish different frequencies to separate sub-bands five types of signals in the EEG recording, which are alpha, beta, gamma, delta, and theta as mentioned above. A filter at the lowest level divides the frequency range in half and produces high pass (detail coefficient) and low pass results (approximation coefficient).

We then run the approximation coefficient through the filter. This is repeated until the target frequency ranges aren't met. Filter banks are so named because the filters are applied sequentially. The procedure is repeated for each channel. We retrieve entropy and energy for every sub-band, namely, 10features for each channel, in each iteration for 62 channels. The feature extraction is finished, for each EEG Pre-processed signal, signaling 620 features.

A specific spectral component appearing at any given time might often be of great relevance. In these circumstances, knowing the time intervals at which these specific spectrum components occurcan be quite useful.

For instance, in the EEGs, the latency which concerns the event-related potential (ERP) is always of isolated interest (ERP is known as the brain which response to a specific stimulus, such as a flashlight, and the known latency of this reaction is the start of the stimulus and the length of time elapsed between. The wavelet transform can provide both time and frequency information at the same time, resulting in some kind of representation of time-frequency using such a signal.

3.3 FEATURE REDUCTION

PCA is very much an eigenvector-based statistic method that uses singular value decomposition to transform a set of correlated training data into mutually statistically independent training features, known as principal components or PCs.

Principal Components Analysis Procedure:

(1) Mean Normalization of feature

(2) Creating a Covariance Matrix

(3) Determining the Eigen Vectors

(4) Obtain the minimized features or primary components.

3.4 SUPPORT VECTOR MACHINE

Support Vector Machine which is also abbreviated as SVM is a famous Supervised Learning technique for Regression and Classification. However, it is mostly utilized in Classification techniques using Machine Learning.

The purpose of the SVM algorithm is to find the decision boundary and the finest line which divides an n-dimensional space into categories where we can easily place the fresh data points in the proper category in the next coming solutions. This kind of optimal decision boundary is referred to as a hyperplane.

Support Vector Machine chooses the maximum pts that aid in the creation of the hyperplane. These maximal examples are referred to as the support vectors and the method is known as the SupportVector Machine.

Consider the diagram below, which shows two distinct categories separated by a hyperplane: Hyperplane: Multiple lines/decision boundaries can be used to separate classes in n-dimensional space,but we must select the optimal decision boundaries which help to recognize and classify points. Theoptimal boundaries are referred to as the SVM hyperplane.

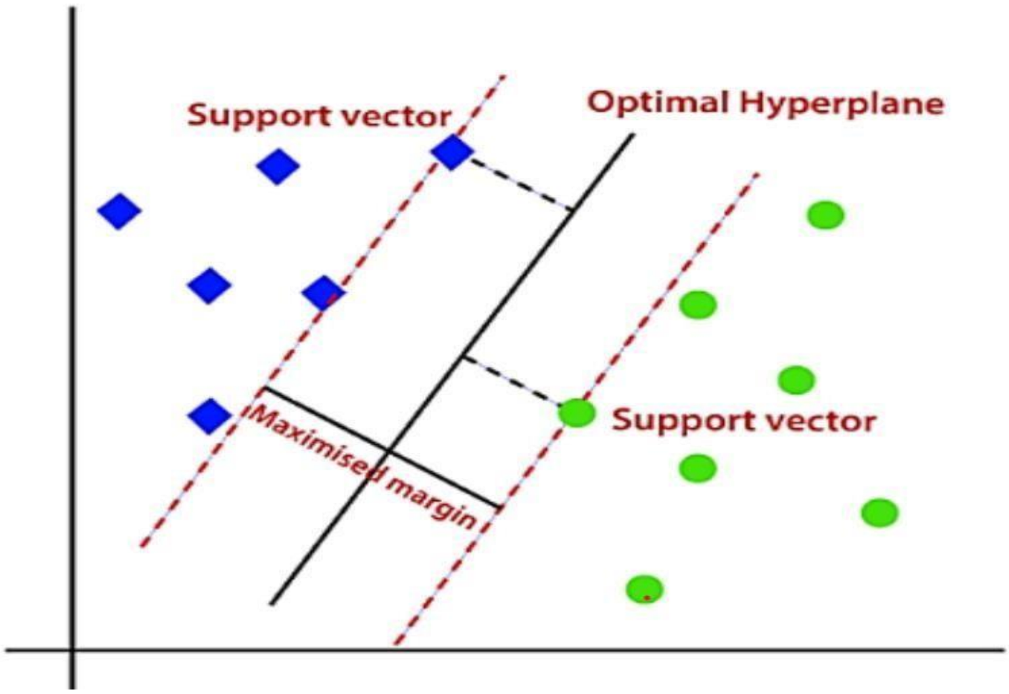


Fig.3.2 : Support vector Machine

The dimensions of a hyperplane are determined by the number of selected features, which implies that if there are only two aspects (as shown in the image), the hyperplane will become a straight line.

But if there are three characteristics, the hyperplane is a two-dimensional plane. We always make a hyperplane with a maximal margin, which indicates the greatest possible difference between the actual points.

The following are the benefits of support vector machines:

• Successful in high-dimensional environments.

• Still effective if the number of dimensions is much larger than the number of samples.

Selects a subset of training examples in the decision boundary (calledsupport vectors), making it memory efficient.

The decision function can be provided with several Kernel functions. The downsides of supportvector machines are as follows:

If the number of features is significantly more than in the sample size,avoid over-fitting while selecting Kernel functions and regularization terms.

SVMs don't immediately provide probability estimates; these are obtainedthrough a costly five-fold cross-validation procedure.

Chapter 4

FPGA-BASED IMPLEMENTATION OF EIGENVECTOR CALCULATION

This chapter discusses the Eigenvector computation implementation. To obtain the Eigenvalues of a matrix, we must first compute the square root, whole square, adder, and subtractor. Employing the CORDIC Square root algorithm simplifies the process because calculating the square root of a number is difficult, A VHDL code and a test bench were built to determine the Eigenvalues of a 2*2 matrix. The programs were executed on Xilinx 14.5 software to ensure functionality and testing. The methodology for the FPGA implementation of Eigenvector calculation is shown in Figure 4.1.

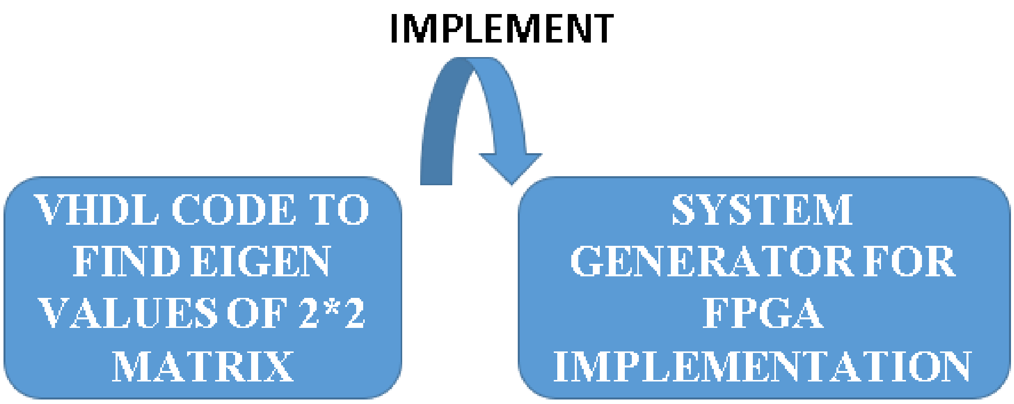


Fig 4.1: Methodology for FPGA Implementation

4.1 CORDIC SQUARE ROOT ALGORITHM

They only require iterative shift-add operations, CORDIC (COordinate Rotation DIgital Computer) based techniques are among the most hardware-efficient algorithms. The CORDIC algorithm avoids the requirement for explicit multipliers and can calculate a wide range of functions.

The important aspect of the systems to achieve approximation for determining the root of variety x is the transition of a floating-point range from base four victimization binary range notation.

Table 4.1: Example of computing square root of algorithm

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

A system generator was chosen for the implementation on an FPGA and a hardware model was generated which shows that the Implementation works on a chip. As the code was written for 18 bits and there are 4 inputs it is difficult to obtain the output on any locally manufactured FPGA boards. JTAG chip support which is the ipcore, ICON (Integrated Controller), and ILA (Integrated Logic Analyzer) are not available in locally manufactured FPGA boards. A Simulink model was designed forthe implementation. After giving the input values, the model runs to give the eigenvalues of that particular matrix and a hardware model is generated. This hardware model can be used in any chip design as a module for any other further work to calculate the eigenvalues

4.2 SYSTEM GENERATOR

Essentially, System Generator allows the designer to spend less time describing and simulating the circuit. On either hand, its design is adaptable; it is feasible to adjust the design specifications and immediately assess the impact on the system's performance and architecture. Such functional simulation is achievable even before the model is compiled.

The compilation creates files containing the system's structural description in a standardized specification language for such ISE which is known as Integrated System Environment on Xilinx FPGAs.

The Gateway out and Gateway In blocks define an FPGA boundary inside the Simulink model. On the Simulink model, the Gateway In blocks transforms floating-point inputs to a fixed-point format; the designer can specify saturation and rounding modes. A Gateway Out block transforms the fixed-point format of the FPGA into a double numeric floating-point numbers format of Simulink. Figure 5.7 shows the Simulink model to calculate the eigenvalue of a 2*2 matrix

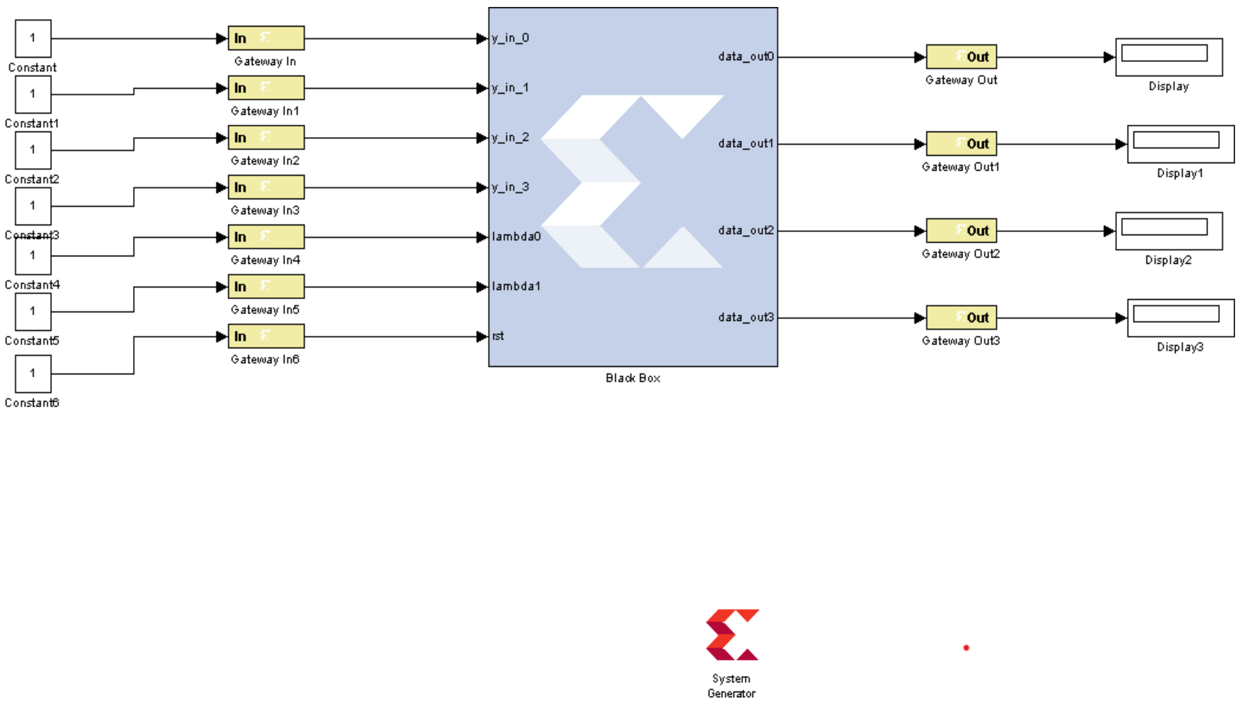


Fig 4.2: Simulink Model for Eigen Vector Calculation in a system generator

The engineer does not view the signals as bits in the System Generator; instead, the bits were arranged in signed as well as the fixed-point format which is unsigned. Operators cause signals to shift to the correct form inside of the outputs automatically. Blocks are not necessarily physical circuit; it interacts along with different blocks to assemble the necessary hardware.

The engineer has an option to include blocks that are defined in an HDL also known as the hardware description language and also a state machine flow diagram, Matlab documents, and so on. The System Generator models are cycle-accurate & bit accurate, which means that simulation outcomes exactly match the hardware outcomes. Signals of Simulink are displayed as values offloating-point numbers, making them effortless to read.

System Generator blocks which can be accessible in the Simulation software library browsers, within Xilinx Toolbox -> HDL) are being used in the design, and the following aspects should be kept in mind: The logic must be housed in a subsystem.

- The Gateway out and Gateway in blocks must be used to indicate the created IP's input/output ports.
- Only modules from the Xilinx Toolbox/HDL library must be used between the Gateway blocks.
- As either a control panel for simulating and IP generation, a System Generator block must be implemented.

4.3 SOFTWARE REQUIREMENTS

4.3.1 PYTHON

Fig 4.3: Python logo

Python programming is a general-purpose language that is high-level of that is interpreted. By making usage of considerable indentation the design of this language prioritizes the readability of its code. For both large-scale and small-scale applications, the language elements, as well as the object- oriented approach, assist programmers in writing the simple, logical code for which it is intended todo.

Python can be frequently used within machine learning projects and artificial intelligence, thanksto packages such as Pytorch, TensorFlow, Scikit-learn & Keras. Python is frequently used for language processing because of its syntax which is very simple and the processing features which are rich along with the modular architecture that it possesses.

4.3.2 XILINX 14.5

Fig 4.4: Xilinx logo

Xilinx provides commercial, industrial, military, & space-grade equipment to the aerospace and defense industries. FPGA prototyping provides rapid and precise SoC system modeling and embedded software verification.

4.3.3 MATLAB

Fig 4.5: MATLAB logo

A MATLAB Simulink add-on provides facilitates for creation of architectural style FPGA designs through the use of graphical block programming.

- With multidomain simulation and modeling, you may explore a large design area and evaluate your systems early on.
- Rapidly assess various design concepts in a single multidomain simulation environment.
- Simulation software larger network models using reusable components and frameworks, as well as third-party modeling tools.
- Deploy desktops, authentic, and Hardware-in-the-Loop simulation models.

4.4 ADVANTAGES

It is beneficial and necessary for safety and healthcare purposes. It is also critical for the quick and easy detection of human emotions at a given time without having to question them. It assists employees and the HR (Human Resources) department of any organization in managing stress levels.

This will foster a safe and healthy workplace and boost productivity. HR and executives will be able to identify positive and bad moods among employees and consumers, allowing firms to develop.

Adoption of technology doesn't necessitate the purchase of any additional pricey hardware. The task of emotion-sensing will be aided by AI recognition software. Real-time voice-based emotion analysis enables automated customer care agents to recognize the emotional experience of callers. Thisallows it to adapt properly.

Emotion recognition has already been commonly utilized by businesses to evaluate consumer sentiment toward their commodities, trademarks, marketing initiatives, employees, or on-site interactions. Understanding client emotions are critical for ensuring business growth and improving experiences, but the potential provided by this technology extends beyond market analysis and online marketing.

Emotion detection using technology was considered a difficult undertaking, but deep learning techniques have shown remarkable promise. Businesses can use Facial Emotion Recognition to scan pictures and videos are true for monitoring live video or automated video surveillance, saving money and making life easier for their users.

We used psychology, human expressions, and intelligent systems to automatically discern significantly change expressions on an individual's face. Our face analysis tool can detect up to seven distinct sorts of emotional states throughout real-time time and it does so anonymously, guaranteeing that individuals' privacy is always maintained

For centuries, humans have recognized facial expressions and detected emotions. However utilizing these signals for business gains and service enhancement is novel. Though recognizing faces and detecting expressions with technology is difficult, the introduction of face detection and emotion recognition systems has made this achievable. Furthermore, for increased accuracy, these algorithms are constantly trained and fed data.

4.4.1 SECURITY METHODS

Emotion recognition has already been utilized in learning institutions since it helps to prevent violence and enhances overall security.

4.4.2 HELP WITH HR

As HR assistants, some firms deploy AI with emotion detection API skills. The algorithm aids in identifying whether a candidate is sincere and genuinely interested in the position byanalyzing intonations, facial expressions, and keywords and producing a report for human recruiters to review.

4.4.3 CHILDREN WITH DIFFERENT ABILITY

A project using a mechanism in Smart Glasses tries to assist autistic children in interpreting the feelings of those around them. When a youngster interacts with others, he or she receives cues about the other person's feelings.

4.4.4 HEALTHCARE

Nowadays, face expression detection is being used extensively in the healthcare industry. They are using it to determine if a victim needs medication or to help physicians decide who to see first.

4.5 APPLICATIONS

It enables the spread of technology into fields such as e-learning, cyber worlds, virtual worlds and entertainment, virtual worlds, cyber worlds, and so on. In the emergence of new areas of human in human-driven interaction with electronic media, automated emotion identification by using EEG signals is gaining awareness.

Medical professionals would be able to analyze their patients' mental health and provide more helpful feedback to help them improve their health. The army will be capable of teaching their soldiers in simulated environments and assessing their mental states in battle situations.

There are three key uses of emotion recognition technologies that use EEG signals:

- First, observance of human emotions while performing certain assignments and measuring neurobiological responses in important moments. The emotion recognition system, for example, concentrates on analyzing a driver's performance during the competition.
- Then, with suitable pharmacological prescriptions or treatment, clinical use in monitoring patients' psychological conditions. Emotion recognition is used in hospital environments to encourage relaxation and stress reduction. The design framework includes three types of emotional services: rest, entertainment, and excitement.
- Finally, emotion recognition has the potential to be employed in the advertising campaign. Emotion recognition can be used for website enhancement, with the system architect to obtain data on which advertisements draw the most awareness, allowing appropriate material to be catered to spectators' demographics.

The cognitive method of emotional recognition of facial gestures, gestures, and vocal characteristics has proven to be superior. Machine perception emotion recognition devices are susceptible to false emotions and are easily exploited.

Many efforts have investigated biomedical parameters which also include the multimodal approach, which combines dissimilar physiological data from biosensing devices like an ECG, electroencephalography (EEG), an electromyogram abbreviated as EMG, and electrodermal activity which is also abbreviated as EDA. But even though the multichannel emotion recognition approach often outperformed the unimodal strategy in terms of processing time and data gathering simplicity.

The use of emotion detection in military therapy was investigated. Because members of the armed services are regularly subjected to an enormously stressful scheme and environment, psychiatric mental disorders such as post-traumatic stress disorder (PTSD), suicidal tendencies, and depression are suffered by most of them.

We should avoid sending unstable emotional troops on dangerous missions, the work advocated using recognition system screening to check the subject's status of mental health. The respondents' reactions to stressful emotions were also examined by the system. Nevertheless, future development is mandatorily needed before any practical application can be realized.

In a smart city, as it is called, an emotion detection system was used to improve the patient e-healthcare systems. Medical doctors have difficulty identifying and regulating the level of pain felt by their patients, particularly those who are unable to express it vocally, such as babies. As a result, theresearchers have proposed a unique monitoring system that was based on an architecture of emotion detection. Through emotion monitoring, the algorithm is capable of producing a detailed tailored indexfor pain detection. With perfect analysis, the outcome of the algorithm achieves a precision of roughly90% when utilizing SVM classification techniques.

Chapter 5

RESULTS

The design was successfully executed in python, Xilinx 14.5, and implemented on a system generator to classify the emotions using SVM algorithms as well as to check the working of the eigenvalue calculation by using the CORDIC square root algorithm. The step-by-step results that were obtained are shown as follows

5.1 RESULTS OBTAINED IN JUPYTER NOTEBOOK

The dataset used here is the SEED dataset. The dataset consisted of 45 Matlab files which comprised 10 features and 62 channels, having a total of 620 features. Preprocessing is carried out in the first stage to remove any unwanted noise which could affect the classification of the emotions. During the feature extraction stage, the use of wavelet filter banks to separate the electroencephalographic pre-processed input into 5 frequency sub-bands. The wavelet transform's filter banks technique is employed to distinguish different frequencies to separate sub-bands five types of signals in the EEG recording, which are alpha, beta, gamma, delta, and theta as mentionedabove. A filter at the lowest level divides the frequency range in half and produces high pass (detail coefficient) and low pass results (approximation coefficient).

The next step is to reduce the features and then classify them, here a set of correlated training data are reduced into mutually statistically independent training features, known as principal components. The mean normalization of features Calculation the Covariance Matrix then determining the Eigen Vectors of that matrix. The highest Eigenvalue is considered the principal component.

The Results obtained in the Jupyter notebook for Principal component analysis are depicted in Fig 5.1.

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

Fig 5.1: The Principal Component Analysis output

After getting the principal component, the data is fed further into SVM for emotion classification. -1 signifies negative emotion, 0 signifies neutral emotion and 1 for positive emotion. The testing set's accuracy is 69 %. The results obtained for SVM classification are shown in Figure 5.2.

```
In [117]: X=seed.iloc[:,:-1].values
          y=seed.iloc[:,-1].values

In [118]: from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

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]]
```

Fig 5.2: The Support Vector Machine Output

The comparison of different ML algorithms is shown in table 5.1.

Table 5.1: Different ML algorithms comparison

	COR	COVMAT	EIGN	ENTROPY	STD	MOMENT	MIN	MEAN	MAX	LOGM	FFT	AVG
LOG REG	65.925	82.555	67.33	60.655	81.145	55.97	89.93	89.11	75.88	83.37	85.595	76.13
SVM	70.795	73.315	69.265	64.955	94.985	50.09	96.98	93.52	88.125	92.38	97.01	81.03
GNB	56.72	48.685	45.6	63.81	47.215	42.225	69.41	83.135	54.72	74.28	70.94	59.70

While comparing the different ML algorithms in the above table, the inference that can be drawn isas follows:

Case 1: Logistic Regression

In this algorithm, the covariance matric value is 82.555, the min value obtained is 89.93, the mean is 89.11, and the max value is 75.88, hence the average obtained in the logistic regression algorithm is 76.13

Case 2: SVM algorithm

In this algorithm, the covariance matric value is 73.15, the min value obtained is 96.98, the mean is 93.52, and the max value is 88.125, hence the average obtained in the SVM algorithm is 81.03.

Case 3: GNB algorithm

In this algorithm, the covariance matric value is 48.685, the min value obtained is 69.415, the mean is 83.135, and the max value is 54.72, hence the average obtained in the Gaussian naïve Bayesalgorithm is 56.70.

By comparing the Logistic regression algorithm and Gaussian Naïve Bayes algorithm, the SVM algorithm outperforms both of them.

5.1 RESULTS OBTAINED IN XILINX 14.5

The VDHL code for a matrix of 2*2 was written for Eigenvector calculation using the CORDIC Square Root Algorithm. To obtain the Eigenvalues of a matrix, we must first compute the square root, whole square, adder, and subtractor.

By employing the CORDIC Square root algorithm, the process gets simplified because calculating the square root of a number is difficult, A VHDL code and a test bench were built to determine the Eigenvalues of a 2*2 matrix. The applications were performed on Xilinx 14.5 software to ensure functionality and testing.

The input values for the matrix are given as Y0= (256,18), Y1= (-512, 18), Y2= (-512,18), Y3= (0,18), lambda 0= (655,18), lambda 1= (-384,18) which is in a Q point representation.

The simulation is performed for the above values to check the functionality and it is tested successfully.

The results obtained are illustrated in Figure 5.3.

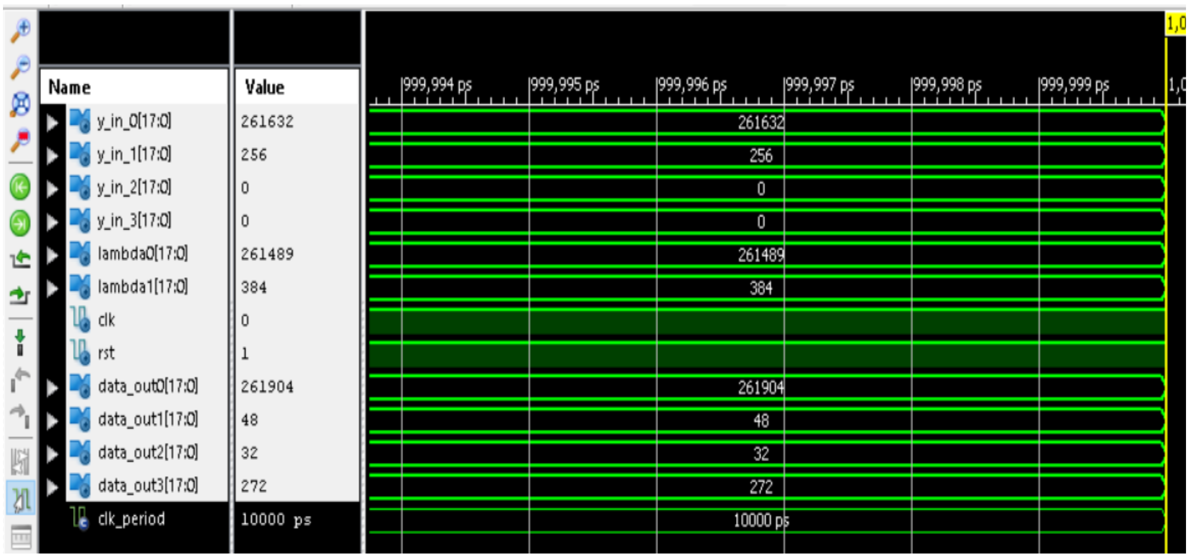


Fig 5.3: Simulation Waveform of Eigen Vector Calculation

The schematic and the RTL schematic of the eigenvector calculation is generated upon simulation. The generated schematics for the calculation of the eigenvector are illustrated in Figure 5.4 and Figure 5.5 respectively.

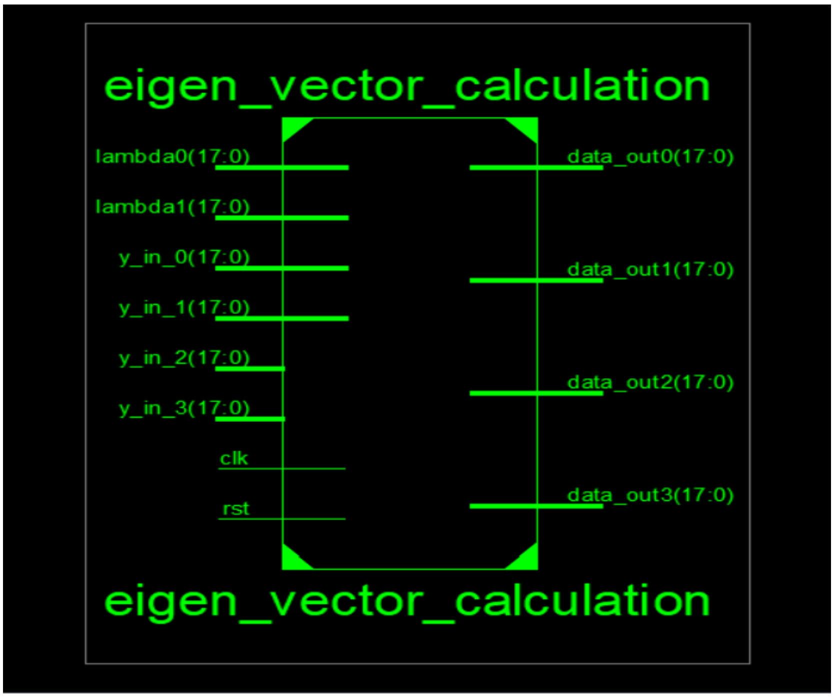


Fig 5.4: Schematic of Eigen Vector Calculation

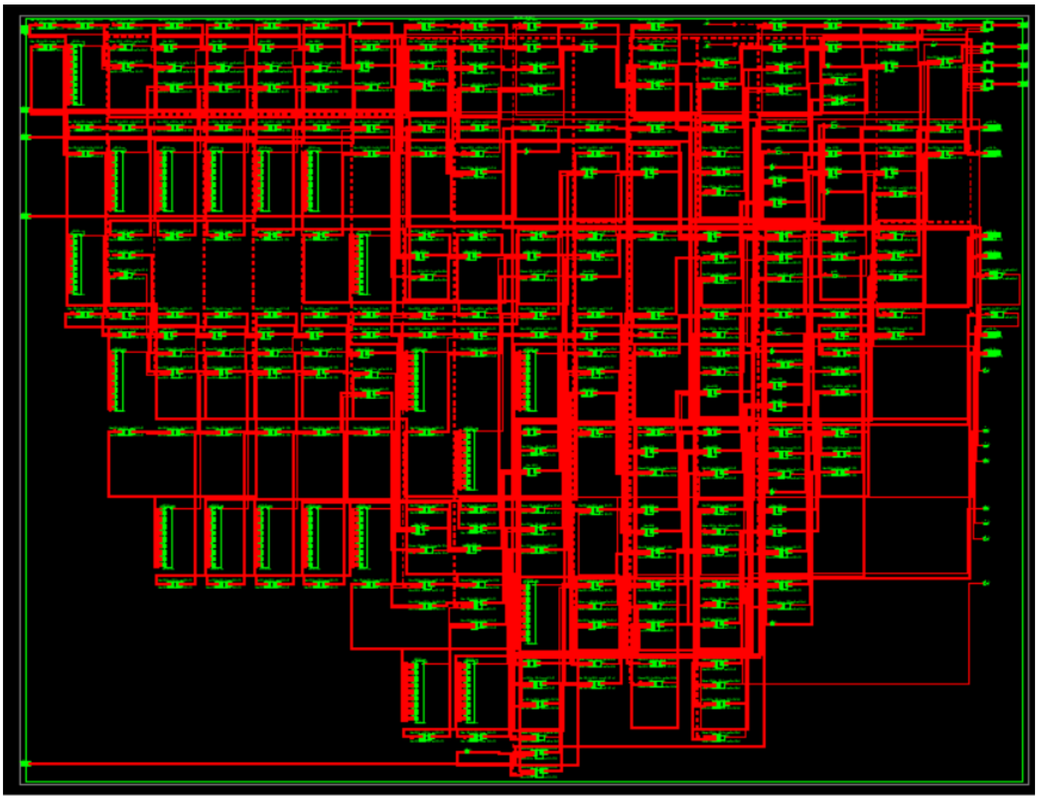


Fig 5.5: RTL Schematic

The logic has occupied 18% of slice LUTs, the usage of fully used LUT-FF pairs is 0%, 66%for the total number of bonded IOBs, the number of BUFG/BUFHCEs/BUFGCTRL at 6%, and the number of DSP48A1s at 37%. The device utilization summary for the eigenvector calculation is depicted in Table 5.1.

Table 5.2: 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%

5.2 RESULTS OBTAINED IN MATLAB SIMULINK

The model to compute the Eigenvalues was designed. Within the Simulink model, the Gateway Out and Gateway In blocks construct an FPGA boundary. The Gateway In blocks on the Simulink model convert floating-point inputs to fixed-point format; the developer can determine saturation and rounding techniques. A Gateway Out block converts the FPGA's fixed-point format to Simulink's double numeric floating-point integers format. The VHDL code is fed into the black box for giving real-time values. The eigenvalues are displayed on the display box as display, display 1, display 2, and display 3 for the 2*2 matrix. The Simulink model for eigenvector calculation is shown in figure 5.7.

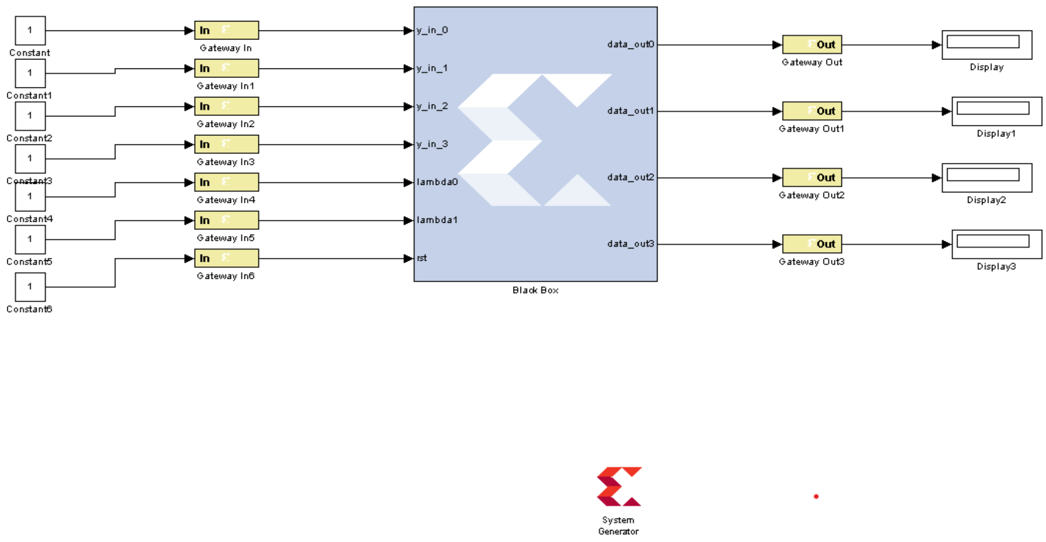


Fig 5.6: Simulink Model for Eigen Vector Calculation

The hardware module generated on a System generator for Eigen Vector Calculation is shown below:

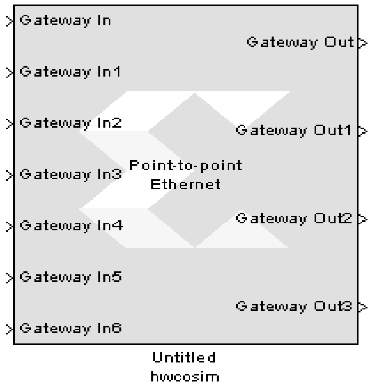
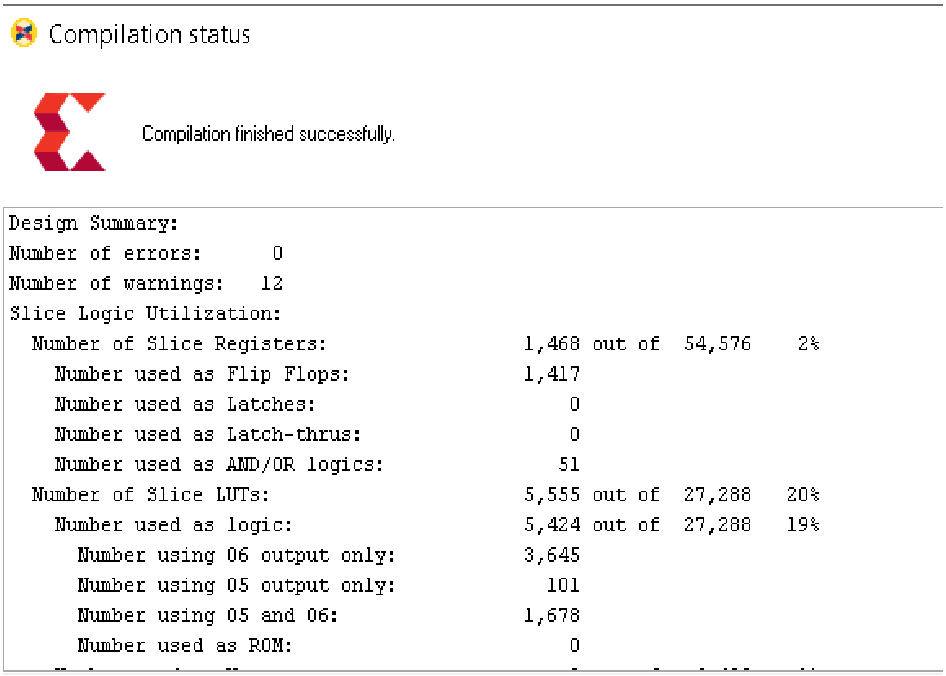


Fig 5.7: Hardware model generated in Simulink

The design summary was generated after the simulation of the model was completed. The design summary gives us insight on actually how many slice registers are utilized, the latches, AND/ logic, and the number of slice registers. Here, 1,468 out of 54,576 slice registers were utilized and itis 2%. The number of slices LUTs used was 5,555 out of 27,288 which accounts for 20%. The Design summary is shown in figure 5.8.




```
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
```

Fig 5.8: Design Summary in Simulink Model

CHAPTER 6

CONCLUSION & FUTURE SCOPE

6.1 CONCLUSION

Using the 'preprocess' function the data is filtered to a frequency range of 0 to 75 Hertz. It produces a unique matrix with a sampling frequency of 200Hz as well as a frequency range of 0 to 75Hz. Eventually, feature extraction is finished, for each EEG preprocessed data yielding 620 features. We apply Principal Component Analysis, or PCA, throughout the feature reduction step.The principal component analysis is an eigenvector-based statistic method that uses singular value decomposition to turn a set of correlated data into independently uncorrelated training features or PCs. Steps to Implement Principal Component analysis (PCA Analysis (1) Feature Mean Normalization (2) Covariance Matrix (3) Determine the Eigen Vectors (4) Determine the simplified features or major components The previous step's PCs will be passed further into the SVM classifier as output. A VHDL code & test bench for a 2*2 matrix was written and the waveform, RTL schematic was obtained on Xilinx 14.5. For the FPGA implementation, the Simulink Model was designed and the eigenvalues were computed using a system generator.

6.2 FUTURE SCOPE

The novel way applies to a very large range of signal processing and artificial intelligence applications. For improved performance, the PCA design can be used with various compressing and dimensionality reduction algorithms. It can as well as be used for real-time applications.

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APPENDIX -A

1. "SILICONS", Inter-collegiate Project Expo, RNSIT Bangalore.


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Channasandra, RR Nagar Post, Bengaluru, 560 098
Department of Electronics and Communication Engineering
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OF SJBIT
For securing II position in SILICONS Intercollegiate VLSI project expo
held on April 29, 2023
Domain -FPGA/Embedded/VLSI Design
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preaching VLSI
Spruha Build-in Solutions
SOLUTIONS

2. **Two days National Level Hands-on Workshop on "India's Indigenous VEGA Processor and Ecosystem".**

3. **Our Project has been patented in <u>OFFICIAL JOURNAL Of THE PATENT OFFICE</u>**

पेटेंट कार्यालय
शासकीय जर्नल

OFFICIAL JOURNAL
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निर्गमन सं. 43/2022	शुक्रवार	दिनांक: 28/10/2022
ISSUE NO. 43/2022	FRIDAY	DATE: 28/10/2022

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PUBLICATION OF THE PATENT OFFICE

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(43) Publication Date : 28/10/2022

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(62) Divisional to Application Number	:NA
Filing Date	:NA

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(57) Abstract :
An electroencephalogram is a machine that uses small metal washers or electrodes positioned on the scalp to identify all the electrical energy in the human brain. Electric impulses connect the brain cells and are always active and even while we are sleeping. This activity appears as wavy lines on the EEG recording. The pre-process function filters data to a frequency range of 0 to 75 Hz. It creates a new matrix with a sampling rate of 200Hz and a range of 0 to 75Hz. The Low pass filter of Finite Impulse Response was utilized. Because band pass would make the EEG data unstable after processing. Each EEG pre-processed signal has output, completing the feature extraction. Principal Component Analysis, or PCA, is used in the feature reduction phase. PCA is a statistical process that turns around a correlated set of features into mutually uncorrelated features, or principal components, using singular value decomposition. Principal Components Analysis: (1) Mean normalization of features (2) Covariance Matrix (3) Eigen Vectors (4) Reduced features or principal components. The preceding step's PCs will be passed into the SVM classifier for emotion output. A VHDL code & test bench for a 2*2 matrix was written and the waveform, RTL schematic was obtained on Xilinx 14.5. For the FPGA implementation, the Simulink Model was designed, and the eigenvalues were computed using a system generator.

No. of Pages : 7 No. of Claims : 4

Project Outcome

Year 2022-23

Project Title: "An FPGA Based Implementation of Emotion Recognition using EEG Signals"

Project Domain: FPGA

Sl No:	Factors addressed through project *	Applicable PO's and PSO's	Justification
1.	Research	PO4 & PSO1	Techniques for dimensionality reduction and emotion recognition using EEG signals
2.	Safety	PO6	Fosters a safe, healthy workplace and boost productivity.
3.	Skill	PO1	Feature extraction, classification techniques and Eigen Vector calculation
4.	Technology	PO5	XILINX, MATLAB, PHYTON.
5.	Social relevance	PO6	Healthcare and Security
6.	Economy	PO11	Economical when compared other commercial models.
7.	Teamwork	PO9	Worked effectively as an individual and as a member.

Signature of Students

Signature of Guide