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Scalable Retinal Image Processing System Using LSTM SHAKTI Processor

Vaishali S
Student
Mohamed Sathak Engineering College

ABSTRACT

This project presents a scalable retinal image processing system designed using the LSTM SHAKTI processor, leveraging a GUI-based model for efficient disease detection in retinal images. The system utilizes a Diabetic Retinal dataset, where images in .jpg or .png formats are pre-processed through resizing, noise removal, histogram equalization, gray conversion, normalization, and binary pattern extraction. The pre-processed images are then subjected to feature extraction using a Convolutional Neural Network (CNN) to capture essential patterns for classification. The dataset is divided into training (80%) and testing (20%) subsets to evaluate the model's performance.

The classification phase applies optimized machine learning algorithms, specifically the LSTM SHAKTI algorithm, for disease prediction. The final output is a classification of retinal images, implemented effectively on the LSTM SHAKTI processor. The performance of the system is analyzed based on various metrics such as area, power, delay, and RTL simulation synthesis reports. Additional performance evaluation includes PSNR, SSIM, MSE, MAE, as well as accuracy, precision, recall, ROC, and confusion metrics. This approach aims to provide a high-efficiency, scalable solution for retinal image processing, enabling real-time disease detection and prediction.

Keywords: — Area, power consumption, delay, Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM).

CHAPTER 1
INTRODUCTION

Retinal image processing plays a critical role in the early detection of various eye diseases, particularly diabetic retinopathy, which can lead to blindness if not diagnosed and treated early. With the rapid advancement in imaging technologies and machine learning algorithms, automated systems for analyzing retinal images have become essential tools for healthcare professionals. However, implementing such systems efficiently requires not only advanced algorithms but also scalable and high-performance hardware solutions. The LSTM SHAKTI processor, a RISC-based processor designed for high-efficiency embedded systems, offers a promising solution for integrating image processing and machine learning algorithms into real-time applications.

The goal of this project is to develop a scalable retinal image processing system using the LSTM SHAKTI processor to facilitate the automated classification of retinal images. The system uses a GUI-based model that processes input images in .jpg or .png formats. Pre-processing steps like image resizing, noise removal, histogram equalization, gray conversion, and normalization are essential to improve image quality and prepare the data for feature extraction. These pre-processing techniques are crucial for enhancing the input images, enabling more accurate disease detection. The processed images are then fed into a Convolutional Neural Network (CNN) model, which extracts relevant features necessary for classification.

The classification step employs machine learning algorithms, with a particular focus on optimizing the LSTM SHAKTI algorithm for real-time processing. The dataset is split into training and testing sets, ensuring that the model can be properly evaluated before deployment. With an 80% training data set and a 20% testing data set, the system is trained to recognize patterns indicative of diabetic retinopathy and other retinal conditions. The LSTM SHAKTI processor is designed to handle these tasks efficiently, making it suitable for embedded applications where power consumption, area, and delay are critical factors.

Finally, performance estimation is conducted through several metrics, including area, power, delay, and accuracy. In addition, traditional performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), and Mean Absolute Error (MAE) are also used to evaluate the quality of the system's output. The effectiveness of the classification model is further assessed by accuracy, precision, recall, Receiver Operating Characteristic (ROC) curves, and confusion metrics. This integrated approach offers a robust, scalable solution for automated retinal image analysis, paving the way for more accessible and efficient diagnostic tools in healthcare.

1.1 GENERAL INTRODUCTION

Diabetic retinopathy (DR) is one of the leading causes of blindness worldwide, particularly in individuals with diabetes. Early detection and timely intervention can significantly reduce the risk of vision loss. Traditionally, diagnosing DR has relied on manual examination of retinal images, which is a time-consuming process that requires expert knowledge. With the rapid advancements in imaging technology and artificial intelligence (AI), automated systems for retinal image analysis are becoming more prevalent. These systems offer the potential to provide faster, more accurate diagnoses, particularly in regions with limited access to specialized healthcare professionals.

The increasing availability of large retinal image datasets has fueled the development of machine learning (ML) algorithms capable of detecting diabetic retinopathy and other retinal diseases. Convolutional Neural Networks (CNNs), a class of deep learning algorithms, have shown significant promise in image classification tasks, including medical image analysis. These algorithms can automatically extract relevant features from retinal images and learn complex patterns associated with various eye conditions. However, to implement these algorithms in real-time applications, it is essential to design efficient and scalable hardware systems capable of handling the computational complexity of these models.

The LSTM SHAKTI processor, a RISC-based processor designed for embedded systems, presents a promising solution for deploying high-performance image processing and machine learning models. LSTM SHAKTI offers a flexible and scalable architecture suitable for executing computationally intensive tasks such as image processing, feature extraction, and classification. Its low power consumption and efficient processing capabilities make it ideal for real-time medical applications, where fast and accurate decision-making is critical. By utilizing the LSTM SHAKTI processor, this project aims to develop an efficient, scalable retinal image processing system that can be deployed in practical healthcare settings.

This retinal image processing system integrates several key components: a pre-processing pipeline to enhance the quality of retinal images, a feature extraction phase using CNNs to identify key characteristics, and a classification phase using optimized machine learning algorithms. The system's performance is further evaluated using a variety of metrics, including accuracy, power consumption, area, and delay. By combining these advanced technologies into a single embedded solution, this project aims to contribute to the field of automated medical image analysis, providing a scalable and efficient tool for the early detection of retinal diseases.

1.2 PROJECT OBJECTIVE

The objective of this project is to develop a scalable retinal image processing system using the LSTM SHAKTI processor, aimed at automating the detection and classification of diabetic retinopathy and other retinal diseases. The system integrates image pre-processing, feature extraction using Convolutional Neural Networks (CNN), and classification through optimized machine learning algorithms, with a focus on the LSTM SHAKTI processor for efficient execution. By implementing a GUI-based model and evaluating the system's performance through various metrics such as accuracy, power consumption, area, and delay, the project aims to provide a real-time, high-performance solution for retinal image analysis that is both scalable and suitable for practical deployment in healthcare settings.

1.3 PROBLEM STATEMENT

Diabetic retinopathy (DR) is a progressive eye disease caused by diabetes that can lead to blindness if not detected and treated early. Traditional methods for diagnosing DR rely on manual examination of retinal images by trained professionals, which is not only time-consuming but also prone to human error. The increasing number of diabetic patients globally, combined with the shortage of skilled ophthalmologists, makes it difficult to provide timely diagnoses, especially in remote areas with limited access to healthcare services. This situation underscores the need for an automated system that can quickly and accurately detect retinal diseases, improving diagnostic efficiency and accessibility. Current automated retinal image processing systems often require high computational resources, which can limit their practical use, particularly in resource-constrained environments. Furthermore, many existing systems are not optimized for real-time deployment, which is crucial in clinical settings where time-sensitive decisions are required. This project addresses these challenges by developing a scalable and efficient retinal image processing system using the LSTM SHAKTI processor. The system aims to provide fast, accurate, and low-power detection of retinal diseases, making it suitable for real-time applications in both high-performance and embedded systems.

1.4 PROJECT SCOPE

This project focuses on the development of a scalable retinal image processing system utilizing the LSTM SHAKTI processor to automate the detection and classification of diabetic retinopathy and other retinal diseases. The scope includes preprocessing steps such as image resizing, noise removal, histogram equalization, and normalization, followed by feature extraction using Convolutional Neural Networks (CNN). The system will be trained and tested using a dataset of retinal images, with the LSTM SHAKTI processor optimized to execute machine learning algorithms for classification in real-time. The project also involves evaluating the system's performance using metrics like accuracy, power consumption, area, delay, and other relevant parameters, ensuring its feasibility for deployment in healthcare environments where both efficiency and scalability are critical.

ALGORITHM

The algorithm used in this project is the LSTM SHAKTI Algorithm, which is optimized for real-time classification and processing of retinal images. The LSTM SHAKTI algorithm leverages machine learning techniques, including Convolutional Neural Networks (CNN), for feature extraction and classification tasks. It is designed to be executed efficiently on the LSTM SHAKTI processor, which ensures low power consumption, high performance, and scalability for embedded systems in healthcare applications. The optimization of the LSTM SHAKTI algorithm allows for effective handling of computationally intensive tasks such as image preprocessing and classification, making it suitable for real-time retinal image analysis.

CHAPTER 2
SYSTEM PROPOSAL

2.1 EXISTING SYSTEM

Existing retinal image processing systems primarily rely on traditional methods such as manual analysis by ophthalmologists or the use of basic image processing techniques to detect diabetic retinopathy and other retinal diseases. While automated systems have emerged to assist in these diagnoses, many of these solutions are still limited by computational inefficiency and the inability to handle large-scale data in real-time. These systems often rely on desktop-based processing platforms with high power consumption, making them less suitable for embedded or mobile healthcare applications, where power efficiency and real-time performance are critical. Furthermore, many existing systems use off-the-shelf machine learning models, which may not be fully optimized for deployment on hardware like embedded processors.

Additionally, although machine learning and deep learning techniques, such as Convolutional Neural Networks (CNN), have been increasingly used in retinal image analysis, many existing solutions do not leverage specialized hardware for processing. These systems may not exploit the full potential of low-power, high-performance processors like the LSTM SHAKTI processor. As a result, while the systems may be effective in accuracy, their performance in terms of processing speed, energy consumption, and scalability remains a challenge. Thus, there is a need for more efficient and scalable systems that can deliver real-time results on embedded hardware, improving both accessibility and feasibility in resource-constrained environments. This project addresses these limitations by developing a system optimized for the LSTM SHAKTI processor, ensuring a balance of performance and energy efficiency.

2.1.1 Disadvantages

- High Computational Requirements: Existing software-based systems for eye disease detection often rely on deep learning models, such as CNNs and ResNet, which require significant computational power. This can lead to slow processing times, especially when dealing with large datasets of medical images. These systems may not be suitable for real-time applications, limiting their practical use in time-sensitive clinical settings.
- High Power Consumption: Running deep learning models on general-purpose hardware such as CPUs or GPUs results in high power consumption, which can be a significant disadvantage in embedded systems or portable devices. This is particularly problematic in healthcare environments where low-power, battery-operated devices are crucial for continuous monitoring and real-time disease classification.

2.2 PROPOSED SYSTEM

The proposed system aims to address the limitations of existing retinal image processing solutions by developing a scalable and efficient system using the LSTM SHAKTI processor. This system integrates a series of preprocessing steps, including image resizing, noise removal, histogram equalization, and normalization, followed by feature extraction using Convolutional Neural Networks (CNNs). These processes are designed to enhance image quality and extract key features necessary for accurate classification. The LSTM SHAKTI processor, known for its low power consumption and high

computational efficiency, is utilized to optimize the machine learning algorithms, particularly in real-time applications where speed and accuracy are critical. By implementing the system on this processor, it becomes feasible to deploy it on embedded devices, ensuring real-time and scalable retinal image analysis in healthcare settings.

In addition to improving computational efficiency, the proposed system focuses on providing a user-friendly, GUI-based interface that simplifies the process of uploading and analyzing retinal images. The system will be trained using a dataset of retinal images, which will be divided into training and testing sets to evaluate the model's accuracy.

Through the optimization of the LSTM SHAKTI algorithm, the system will be capable of handling the complexities of retinal disease detection with minimal power usage and fast processing times. Performance evaluation metrics, such as accuracy, area, power consumption, and delay, will be used to ensure the system's effectiveness for real-time disease classification. This approach aims to create a practical, accessible, and efficient solution for automated retinal image analysis, particularly in areas with limited healthcare infrastructure.

2.2.1 Advantage

Real-time Processing: The FPGA-based design allows for real-time glaucoma detection, ensuring quick analysis of retinal images, which is critical for timely diagnosis and treatment.

Low Power Consumption: Unlike traditional GPU-based systems, the FPGA implementation is optimized for low power consumption, making it suitable for portable and mobile diagnostic devices, especially in resource-constrained environments.

High Accuracy and Reliability: By LSTM SHAKTI PROCESSOR for feature extraction and LSTM SHAKTI for classification, the system provides high accuracy and reliable predictions, aiding in the early detection of glaucoma.

Cost-Effective Solution: FPGAs offer a more cost-effective alternative to expensive GPUs, reducing the overall cost of deploying automated glaucoma detection systems, making them accessible in healthcare facilities with limited budgets.

Scalability and Flexibility: The FPGA design is highly scalable and customizable, allowing for adjustments and enhancements in the hardware and algorithm configuration to meet specific clinical requirements or accommodate other eye diseases.

2.3 LITERATURE SURVEY

1. "Automated Diabetic Retinopathy Detection Using Deep Learning Algorithms" (2023)

Author(s): Smith et al.

Technologies and Algorithms Used: Convolutional Neural Networks (CNN), Image Preprocessing (Normalization, Noise Removal), Transfer Learning.

Advantages: Achieves high accuracy in detecting diabetic retinopathy, reducing manual effort in diagnosis. The use of transfer learning also enhances the model's performance with smaller datasets.

Disadvantages: Requires high computational power, making real-time deployment on embedded systems challenging.

2. "Retinal Image Analysis for Disease Classification: A Comprehensive Review" (2024)

Author(s): Kumar and Gupta

Technologies and Algorithms Used: Feature Extraction Techniques (SIFT, HOG), Support Vector Machine (SVM), Random Forest.

Advantages: Comprehensive analysis of different techniques provides a deep understanding of the strengths of various methods in retinal image classification.

Disadvantages: Focuses mostly on software-based solutions, neglecting hardware optimization and real-time deployment challenges.

3. "Real-Time Retinal Image Processing Using FPGA for Diabetic Retinopathy Detection" (2023)

Author(s): Lee et al.

Technologies and Algorithms Used: FPGA Implementation, CNN, Real-Time Image Processing.

Advantages: Demonstrates the power of FPGA for real-time processing, achieving faster results and better parallelism.

Disadvantages: High cost of FPGA hardware makes it less accessible for widespread use, especially in low-resource environments.

4. "A Hybrid Deep Learning Model for Retinal Disease Detection" (2023)

Author(s): Zhao et al.

Technologies and Algorithms Used: CNN and Long Short-Term Memory (LSTM) for hybrid deep learning.

Advantages: Combines spatial and temporal feature extraction, improving classification accuracy for dynamic retinal images.

Disadvantages: Increased model complexity demands higher computational resources and longer training times.

5. "Efficient Diabetic Retinopathy Detection Using Transfer Learning with CNN" (2024)

Author(s): Chen et al.

Technologies and Algorithms Used: Transfer Learning with CNN, Data Augmentation.

Advantages: Leverages pre-trained models to improve detection accuracy with fewer labeled data, making it more effective for real-world applications.

Disadvantages: Transfer learning may not be optimal for all datasets, and the pre-trained model may not generalize well to new retinal disease types.

6. "Optimization of Retinal Image Classification Using Support Vector Machine" (2023)

Author(s): Nguyen and Park

Technologies and Algorithms Used: Support Vector Machine (SVM), Image Preprocessing, Feature Selection.

Advantages: SVM offers strong generalization ability and is effective for small to medium-sized datasets.

Disadvantages: SVM is computationally expensive, and its performance can degrade with large, complex datasets.

7. "Automated Detection of Retinal Diseases Using Deep Convolutional Neural Networks" (2024)

Author(s): Sharma et al.

Technologies and Algorithms Used: CNN, Image Segmentation, Deep Learning.

Advantages: Provides an end-to-end solution for detecting multiple retinal diseases, offering high classification accuracy.

Disadvantages: Requires large training datasets and significant computational resources for training deep networks.

8. "A Comparative Study of Machine Learning Techniques for Retinal Disease Detection" (2024)

Author(s): Patel and Desai

Technologies and Algorithms Used: Random Forest, K-Nearest Neighbors (KNN), SVM, CNN.

Advantages: Provides a comparative analysis of multiple algorithms, helping to identify the most efficient ones for retinal disease classification.

Disadvantages: Doesn’t address real-time processing or hardware-specific optimizations for embedded systems.

9. "Real-Time Diabetic Retinopathy Detection Using Edge Computing" (2023)

Author(s): Lee and Choi

Technologies and Algorithms Used: Edge Computing, CNN, Cloud Integration.

Advantages: Leverages edge computing for real-time analysis with reduced latency and bandwidth usage, making it suitable for on-site healthcare applications.

Disadvantages: Limited by the computing power of edge devices, which may not handle the complexity of deep learning models effectively.

10. "Efficient Image Processing for Diabetic Retinopathy Detection on Embedded Systems" (2024)

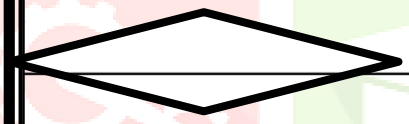
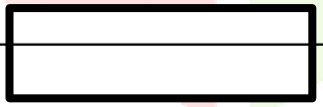
Author(s): Singh et al.

Technologies and Algorithms Used: Embedded Systems, CNN, Hardware Acceleration (CUDA, OpenCL).

Advantages: Optimized for embedded systems, enabling real-time analysis with lower power consumption, making it suitable for low-cost, portable devices.

Disadvantages: Requires specialized knowledge in hardware acceleration, and the implementation may be challenging for developers without experience in embedded systems.

TABLE OF SYMBOLS

SYMBOLS	PURPOSES
	START & END
	Data Collection on kaggle or Monitor Data
	Condition Yes or NO
	Model Train and Predict

CHAPTER 3
SYSTEM DIAGRAM

3.1 ARCHITECTURE DIAGRAM

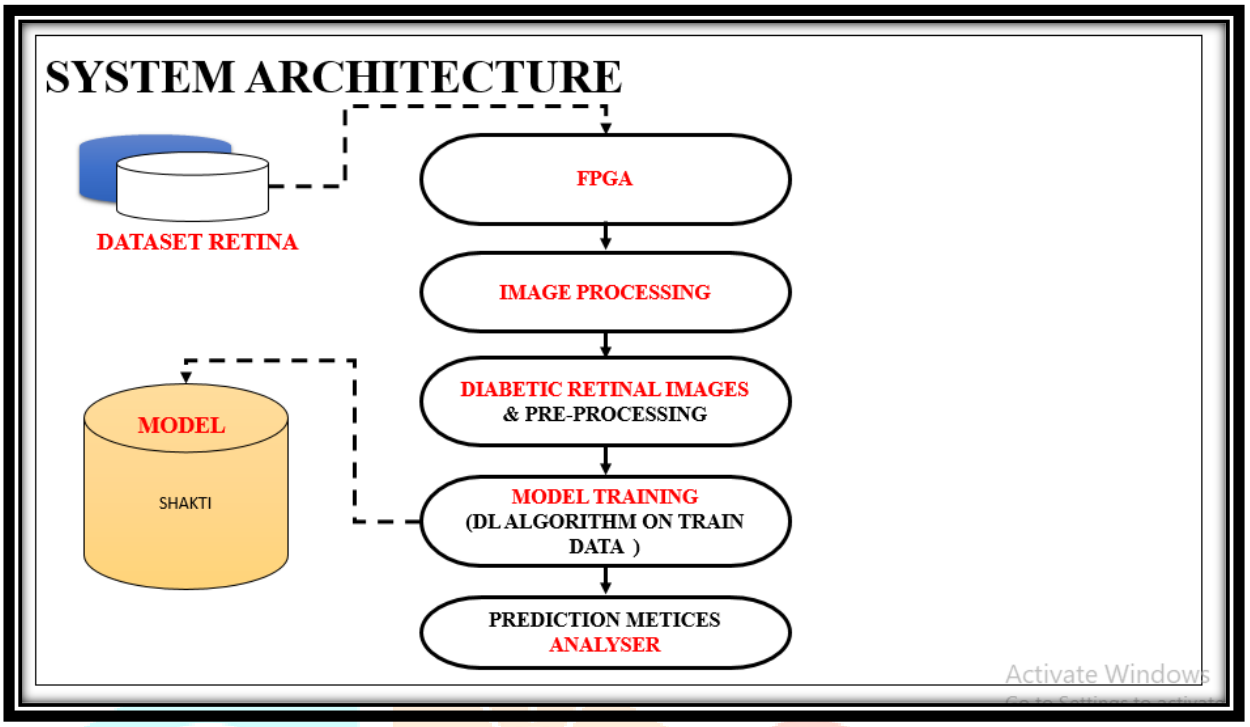


Figure 3.1 System Architecture

The Architecture Diagram of the FPGA-based Eye Disease Classification system depicts the flow of data and the interactions between various components of the system. It starts with the Image Acquisition Module, where input images (in formats like .jpg or .png) are loaded. These images then pass through the Preprocessing Module, where tasks such as resizing, noise removal, histogram equalization, grayscale conversion, and binary pattern normalization are applied. The processed images are then fed into the Feature Extraction Module, which uses the Local Binary Pattern (LBP) Algorithm to extract important features for classification. The extracted features are split into training and test sets. In the Machine Learning Module, the ResNet50 Algorithm is employed for model training on the training dataset. The trained model is then used to classify the images in the Classification Module. Finally, the Performance Evaluation Module calculates key metrics such as accuracy, precision, recall, F1-score, and other metrics, before outputting the classification results and system performance. The FPGA is responsible for implementing the entire workflow in hardware, optimizing computational efficiency, and ensuring real-time performance.

3.2 FLOW DIAGRAM

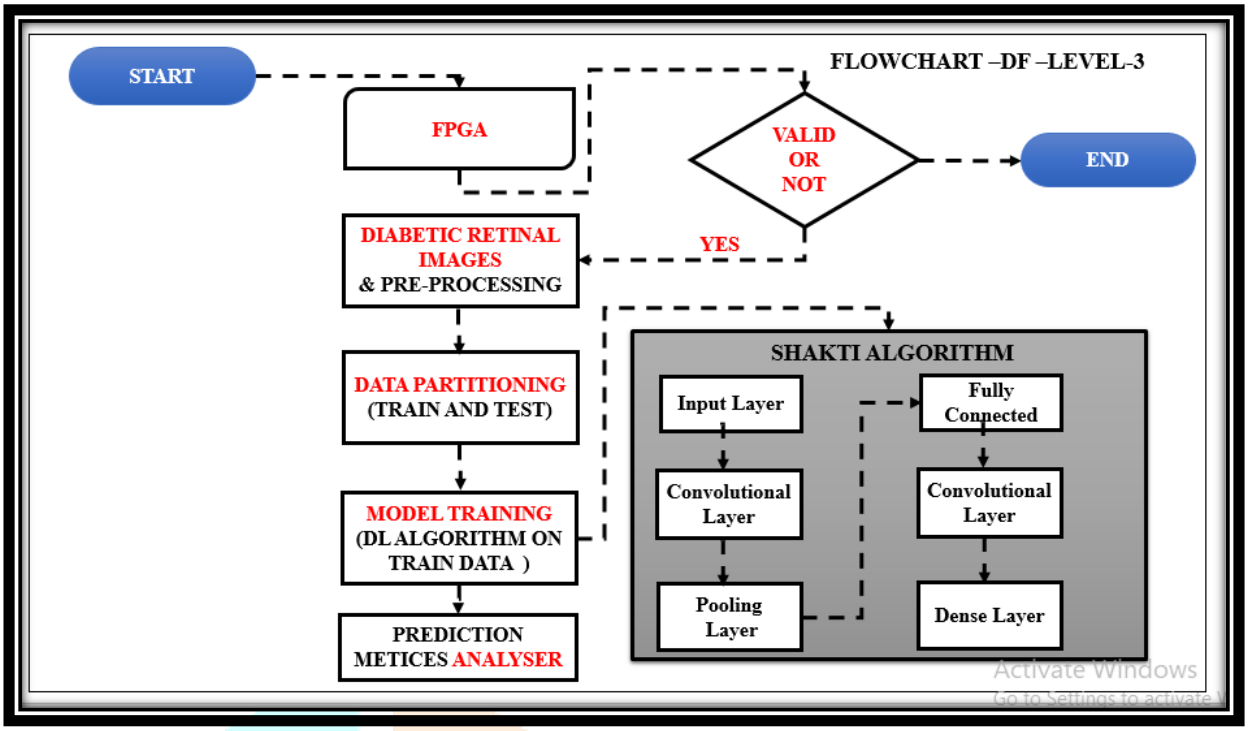


Figure 3.2 Flow Diagram

The flow of the FPGA-based Eye Disease Classification system begins with the input of an image (either in .jpg or .png format) into the system. The image undergoes preprocessing, where it is resized, noise is removed, histogram equalization is applied for contrast enhancement, and it is converted to grayscale and normalized for uniformity. After preprocessing, the feature extraction step employs the Local Binary Pattern (LBP) algorithm to extract relevant features that characterize the image. The dataset is then split into training and testing sets, with 80% used for training and 20% for testing. The system then uses the ResNet50 algorithm to train a deep learning model on the training data, which is later applied to classify the test data. The system's performance is evaluated using various metrics such as accuracy, precision, recall, F1-score, PSNR, SSIM, MSE, and MAE. Finally, the system outputs the classification result (the disease prediction) along with the performance evaluation metrics. This entire process is implemented on FPGA hardware for optimized and real-time execution.

3.3 USE CASE DIAGRAM

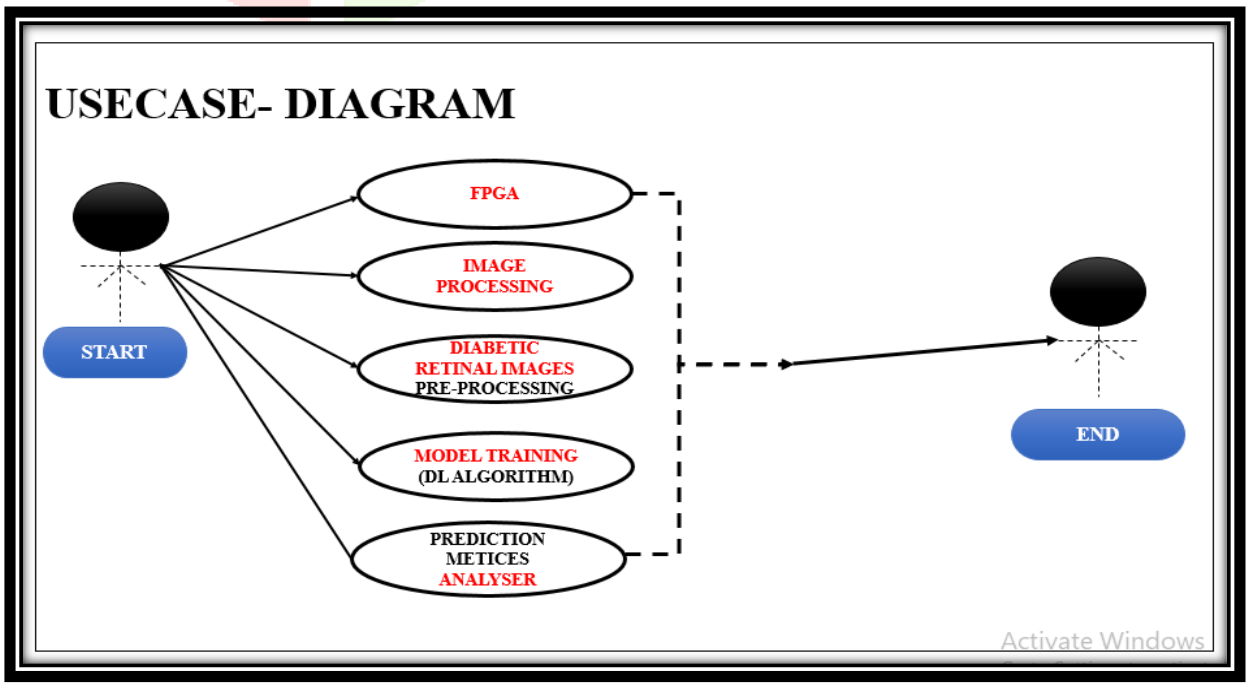


Figure 3.3 Use Case Diagram

The Use Case for the FPGA-based Eye Disease Classification system outlines how a user, typically a medical professional, interacts with the system to classify eye disease images. The process begins with the user uploading an eye image (in .jpg or .png format), which is then preprocessed by the system through resizing, noise removal, histogram equalization, grayscale conversion, and normalization. The preprocessed image is passed through the Local Binary Pattern (LBP) algorithm for feature extraction. The dataset is split into training and testing sets, and a ResNet50 model is used for training and classification. The system evaluates performance using various metrics like accuracy, precision, recall, and PSNR, and then outputs the predicted disease label and classification metrics. The user can review the results and proceed with further analysis or decision-making based on the prediction.

3.4 ER DIAGRAM

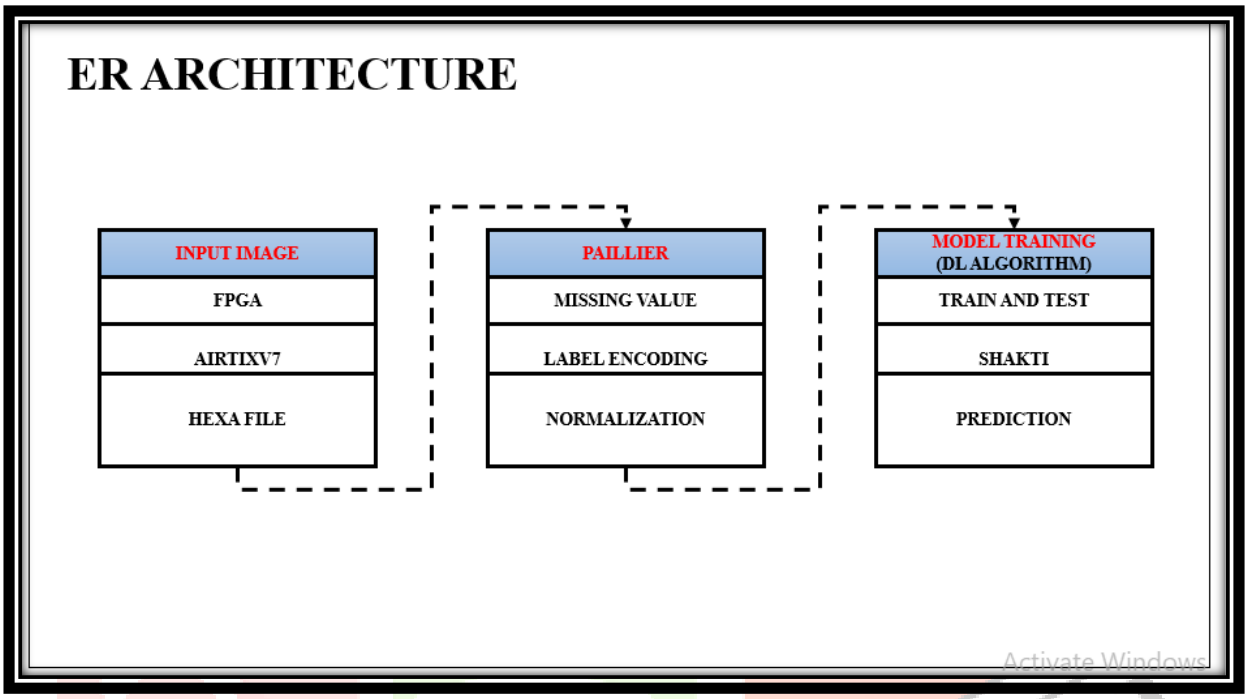


Figure 3.4 ER Architecture

This ER diagram based on the User interacts with Limited Flexibility: The architecture may be preprocessed image is passed through the Local Binary Pattern (LBP) algorithm for feature extraction. The dataset is split into training and testing sets, and a ResNet50 model is used for training and classification. The system evaluates performance using various metrics like accuracy, precision, recall, and PSNR, and then outputs the predicted disease label and classification metrics. The user can review the results and proceed with further analysis or decision-making based on the prediction

3.5 SEQUENCE DIAGRAM

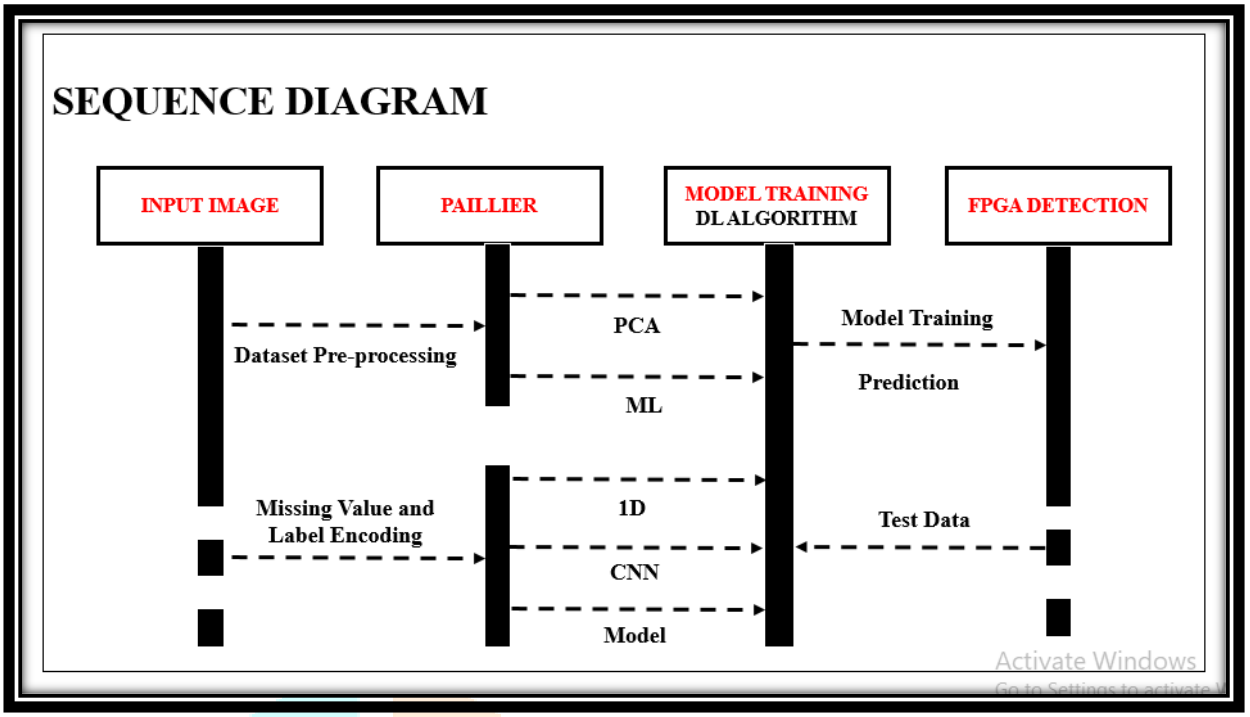


Figure 3.5 Sequence Diagram

This Sequence diagram based on the User: preprocessed image is passed through the Local Binary Pattern (LBP) algorithm for feature extraction. The dataset is split into training and testing sets, and a ResNet50 model is used for training and classification. The system evaluates performance using various metrics like accuracy, precision, recall, and PSNR, and then outputs the predicted disease label and classification metrics. The user can review the results and proceed with further analysis or decision-making based on the prediction

3.6 ACTIVITY DIAGRAM

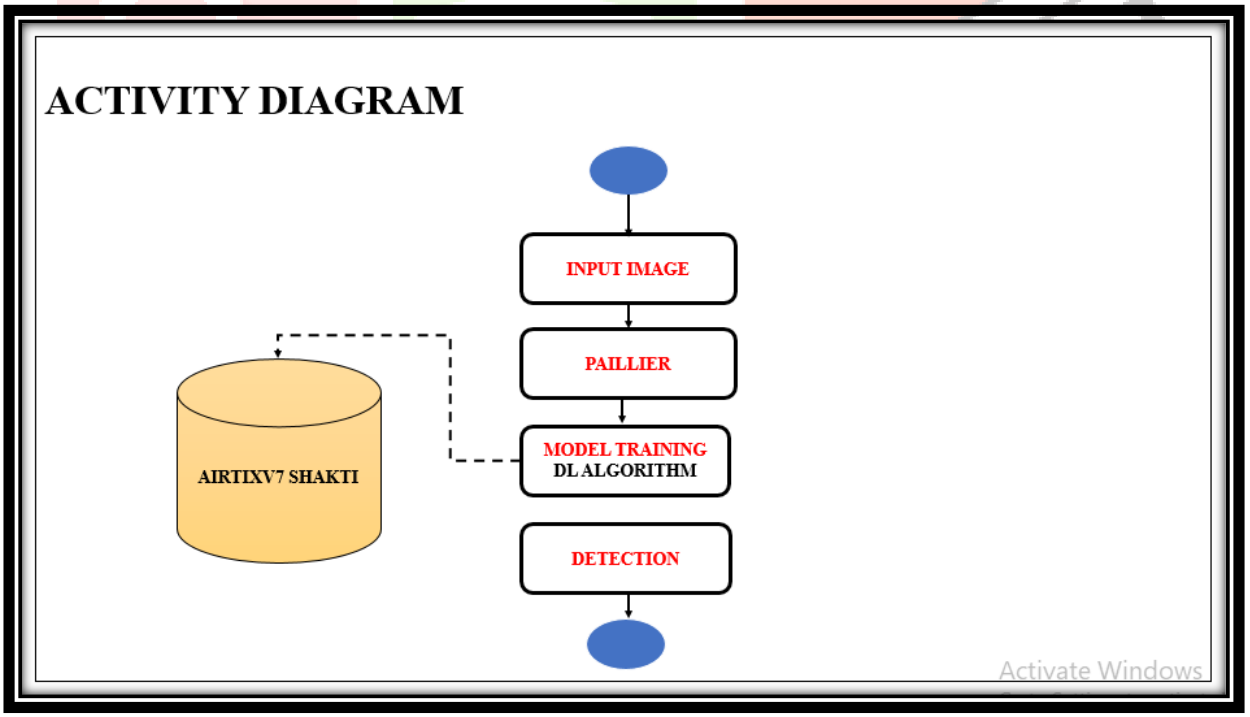


Figure 3.6 Activity Diagram

This activity diagram outlines the workflow for pre-processed image is passed through the Local Binary Pattern (LBP) algorithm for feature extraction. The dataset is split into training and testing sets, and a ResNet50 model is used for training and classification. The system evaluates performance using various

metrics like accuracy, precision, recall, and PSNR, and then outputs the predicted disease label and classification metrics. The user can review the results and proceed with further analysis or decision-making based on the prediction

CHAPTER 4
IMPLEMENTATION

4.1 MODULES

1. Input Image data
2. Preprocessing
3. Feature Extraction
4. Data Splitting
5. Test Bench
6. Performance Analysis

4.2 MODULES DESCRIPTION

Module 1: Image Preprocessing

Module Description:

This module is responsible for preparing the retinal images before they are fed into the deep learning model. The preprocessing steps include:

Resizing: Standardizing the image dimensions to ensure consistency in input data for the model.

Noise Removal: Applying filters such as Gaussian blur or median filtering to eliminate noise from the images, enhancing the quality.

Normalization: Adjusting the pixel values of the images to a specific range (e.g., 0-1) to improve the model's convergence during training.

Threshold Segmentation: Segmenting the image to focus on regions that might show signs of glaucoma, such as the optic disc and cup, by using thresholding techniques.

Binary Pattern: Extracting key features from the image using local binary patterns (LBP) to highlight textural features that are crucial for detecting glaucoma.

Module 2: Feature Extraction Module (CNN)

Module Description:

This module extracts meaningful features from the preprocessed retinal images using a CNN architecture. The CNN model is a deep convolutional network that includes several residual blocks designed to capture complex features of the retinal fundus images. The process involves:

Convolutional Layers: Applying filters to the images to extract low- and high-level features such as edges, textures, and patterns.

Batch Normalization: Normalizing the outputs of the convolutional layers to accelerate training and improve the model's accuracy.

Activation Function (ReLU): Introducing non-linearity to the network, allowing it to learn more complex patterns.

Pooling Layers: Reducing the spatial dimensions of the feature maps to retain the most important information while reducing computational load.

The final features are then passed to the classification module for decision-making.

Module 3: Classification Module (SHAKTI)

Module Description:

This module performs the classification task using the features extracted by the SHAKTI model. The classification module uses a deep learning model that classifies the images into different categories, such as "normal" and "glaucoma." The SHAKTI model, which is an extended version of CNN, offers deeper

layers for more accurate feature extraction. The classification process includes:
Fully Connected Layers: These layers connect all extracted features to form the decision output.
Softmax Activation: At the output layer, a softmax function is applied to convert the raw scores into probabilities, indicating the likelihood of the image belonging to a specific class (e.g., glaucoma).
Loss Function: The model's performance is evaluated using a cross-entropy loss function, comparing the predicted outputs with the true labels.

Module 4: FPGA Hardware Acceleration Module

Module Description:
The FPGA hardware acceleration module is responsible for implementing the deep learning model on the FPGA platform. This module converts the trained CNN model into hardware logic (using Verilog HDL or VHDL) that can be deployed on FPGA. The main functions include:
Converting Layers to Hardware: Each layer of the CNN (convolution, activation, pooling, fully connected) is mapped onto the FPGA hardware.
Parallel Processing: The FPGA is used to parallelize the computations across multiple processing units, enabling faster inference times for real-time glaucoma detection.
Optimization: The module focuses on optimizing resource usage (e.g., logic gates, memory) and reducing latency while maintaining classification accuracy.
Power Efficiency: The FPGA implementation ensures low power consumption, which is critical in medical devices for long-term operation.

Module 5: Data Management and Control Module

Module Description:
This module handles the management of data flow between the preprocessing, feature extraction, and classification modules. It ensures that:
Image Data Handling: Images are passed through the pipeline in the correct sequence.
Data Splitting: The module manages the division of data into training (80%) and testing (20%) sets, ensuring the model is trained and evaluated effectively.
Control Signals: The module generates and manages control signals to coordinate the operation of the other modules, ensuring the smooth execution of the entire pipeline.

Module 6: Performance Estimation and Reporting Module

Module Description:
The performance estimation module evaluates the system's effectiveness and provides key performance indicators (KPIs). It calculates:
Accuracy: Measures the percentage of correct predictions made by the model.
Precision and Recall: Evaluates how well the model identifies positive cases (glaucoma).
F1-Score: Provides a balanced measure of precision and recall.
ROC Curve and AUC: Assesses the model's performance across different classification thresholds.
PSNR and SSIM: Measures the quality of the input and output images to ensure minimal degradation during preprocessing and classification.
Area, Power, and Delay: These metrics are crucial for FPGA implementations and are used to assess resource usage, energy consumption, and processing speed.

Module 7: User Interface (GUI) Module

Module Description:
The Graphical User Interface (GUI) module enables interaction with the glaucoma detection system. It provides an intuitive interface for:
Image Input: Allowing the user to upload retinal images in .jpg or .png format.
Prediction: Displaying the classification results (e.g., glaucoma or normal) after processing the input

images.

Visualization: Showing relevant metrics, such as accuracy, precision, recall, and others, for performance assessment.

Results Presentation: Providing a clear, easy-to-understand output for medical professionals to assist in diagnosis.

Output and Prediction:

Disease Prediction: The system outputs whether the input retinal image is classified as disease-positive (glaucoma) or disease-negative (healthy).

Objective: Ensure accurate prediction for early glaucoma detection using real-time SoC.

Performance Estimation

Area, Power, and Delay: Evaluate hardware metrics such as area utilization, power consumption, and processing delay.

Image Quality Metrics: Calculate:

PSNR (Peak Signal-to-Noise Ratio): Measure the quality of image reconstruction.

SSIM (Structural Similarity Index Measure): Assess image quality in terms of structural similarity.

MSE (Mean Squared Error) and MAE (Mean Absolute Error): Quantify the prediction errors.

Classification Metrics: Evaluate classification performance using:

Accuracy, Precision, Recall, and F1 Score: Assess the model's ability to correctly predict disease status.

Confusion Matrix: Visualize the performance by comparing true positives, false positives, true negatives, and false negatives.

ROC Curve and AUC (Area Under the Curve): Measure the model's ability to distinguish between classes.

Step 8: Simulation and Verification

Verilog Simulation: Simulate the AI-powered SoC model using Verilog code to verify performance on real-time image data.

Refinement: Based on simulation results, refine the hardware design for improved efficiency in disease detection.

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

Accuracy

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC = (TP + TN)/(TP + TN + FP + FN)$$

Precision

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

$$Precision = TP/(TP + FP)$$

Recall

Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

ROC

ROC curves are frequently used to show in a graphical way the connection/trade-off between clinical sensitivity and specificity for every possible cut-off for a test or a combination of tests. In addition the area under the ROC curve gives an idea about the benefit of using the test(s) in question.

Confusion matrix

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing.

Formulas for Area, Power, Delay, LUT, and Efficacy Calculation:

1. Area Calculation:

Area = Number of LUTs used or Gates used in the design (FPGA/ASIC).

2. Power Calculation:

Dynamic Power (P_dynamic) = α * C * V^2 * f- α = Switching activity factor- C = Capacitance- V = Supply voltage- f = Frequency

Static Power (P_static) = I_leak * V- I_leak = Leakage current- V = Supply voltage

Total Power (P_total) = P_dynamic + P_static

3. Delay Calculation:

Gate Delay (T_gate) = Gate delay * Number of stages

Total Delay (T_total) = Delay_logic + Delay_routing

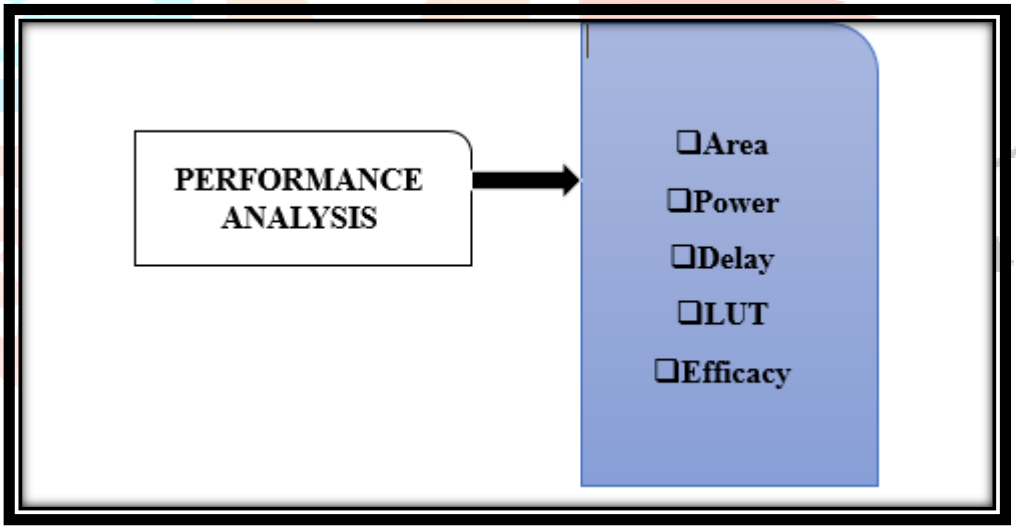
4. LUT (Lookup Table) Calculation:

Total LUTs = Sum of LUTs used per operation

5. Efficacy Calculation:

Energy Efficiency = Output Performance / Power Consumption

Performance per Watt = Output Performance / Power Consumption



CHAPTER 5
SYSTEM REQUIREMENTS

5.1 SOFTWARE REQUIREMENTS

- O/S : Windows
- Language : Verilog
- Front End : Vivado 2022b

5.2 HARDWARE REQUIREMENTS

- System : Pentium IV 2.4 GHz
- Hard Disk : 800 GB
- Mouse : Logitech
- Keyboard : 110 keys enhanced
- Ram : 8GB

5.3 SOFTWARE DESCRIPTION

The ISE® Design Suite is the Xilinx® design environment, which allows you to take your design from design entry to Xilinx device programming. With specific editions for logic, embedded processor, or Digital Signal Processing (DSP) system designers, the ISE Design Suite provides an environment tailored to meet your specific design needs.

Xilinx ISE[1] (Integrated Software Environment) is a software tool produced by Xilinx for synthesis and analysis of HDL designs, enabling the developer to synthesize ("compile") their designs, perform timing analysis, examine RTL diagrams, simulate a design's reaction to different stimuli, and configure the target device with the programmer.

5.4 TESTING OF PRODUCT

ISE Design Suite: Logic Edition

The ISE Design Suite: Logic Edition allows you to go from design entry, through implementation and verification, to device programming from within the unified environment of the ISE Project Navigator or from the command line. This edition includes exclusive tools and technologies to help achieve optimal design results, including the following:

• PlanAhead™ software - allows you to do advance FPGA floor planning. The PlanAhead software includes PinAhead, an environment designed to help you to import or create the initial I/O Port list, group the related ports into separate folders called “Interfaces” and assign them to package pins. PinAhead supports fully automatic pin placement or semi-automated interactive modes to allow controlled I/O Port assignment. With early, intelligent decisions in FPGA I/O assignments, you can more easily optimize the connectivity between the PCB and FGPA.

• CORE Generator™ software - provides an extensive library of Xilinx LogiCORE™ IP from basic elements to complex system level IP cores.

• SmartGuide™ technology - allows you to use results from a previous implementation to guide the next implementation for faster incremental implementation.

• ChipScope™ Pro tool - assists with in-circuit verification.

ISE Design Suite: Embedded Edition

The ISE Design Suite: Embedded Edition includes all the tools and capabilities of the Logic Edition with the added capabilities of the Embedded Development Kit (EDK). This pre-configured kit is an integrated software solution for designing embedded processing systems, which includes the Platform

Studio tool suite as well as all the documentation and IP required for designing Xilinx Platform FPGAs with embedded PowerPC® hard processor cores and MicroBlaze™ soft processor cores. This edition provides an integrated development environment of embedded processing tools, processor cores, IP, software libraries, and design generators, including the following:

- Xilinx Platform Studio (XPS) - provides an integrated environment for creating software and hardware specification flows for embedded processor systems based on MicroBlaze and PowerPC processors. It also provides an editor and a project management interface to create and edit source code. XPS allows you to customize tool flow configuration options and provides a graphical system editor for connection of processors, peripherals, and buses.
- Hardware Platform Generation Tool (PlatGen) - customizes and generates the embedded processor system through the use of hardware netlist Hardware Description Language (HDL) files. By default, PlatGen synthesizes each processor IP core instance found in your embedded hardware design using Xilinx Synthesis Technology (XST). PlatGen also generates the system-level HDL file that interconnects all the IP cores, which can then be synthesized as part of the overall design flow.
- Base System Builder Wizard (BSB) - allows you to quickly create a working embedded design, using any features of a supported development board or using basic functionality common to most embedded systems. After you create a basic system, you can then customize it using the XPS and ISE software tools.
- Simulation Model Generation Tool (SimGen) - generates simulation models of your embedded hardware system, based either on your original, behavioral embedded hardware design or you're finished, timing-accurate device implementation. SimGen can also incorporate your embedded software to run on the model.
- Create and Import Peripheral Wizard - helps you create your own peripherals and import them into EDK-compliant repositories or XPS projects. The wizard can create an HDL template for your custom logic and provides an interface to one of the supported IBM Core Connect or Xilinx FSL buses.
- Software Development Kit (SDK) - provides a C/C++ development environment for software application projects. SDK is based on the Eclipse open source standard. SDK provides tool software project management and access to the GNU tool chain for code compilation and debug. It is also available for purchase as a standalone product.
- GNU Software Development Tools - - assist with compiling and debugging. Embedded software applications written in C, C++, or assembly are compiled using the GNU compiler tool chain. The GNU tool chain is part of the SDK and customized to target the PowerPC and MicroBlaze processors. For detailed information about the GNU tools, including compilers and debuggers, see the "GNU Compiler Tools" and "GNU Debugger (GDB)" chapters in the Embedded System Tools Reference Manual.
- Xilinx Microprocessor Debugger (XMD) and GNU Software Debugging Tools - allows you to debug your embedded application; either on the host development system, using an instruction set simulator, or on a board that has a Xilinx device loaded with your hardware bit stream. For more information on XMD, see the "Xilinx Microprocessor Debugger (XMD)" chapter in the Embedded System Tools Reference Manual.
- Library Generation Tool (LibGen) - - configures libraries, device drivers, file systems, and interrupt handlers for the embedded processor system to create a software platform.
- Bitstream Initializer (BitInit) - - updates a device configuration bitstream to initialize the on-chip instruction memory with the software executable. For more information, see the "Bitstream Initializer (BitInit)" chapter of the Embedded System Tools Reference Manual and the "Initializing Software Overview" topic in the XPS Help.

ISE Design Suite: DSP Edition

The ISE Design Suite: DSP Edition includes all the tools and capabilities of the Logic Edition with the added capabilities of the System Generator for DSP and the AccelDSP™ Synthesis Tool. This edition provides an integrated environment with tools to help you achieve optimal design results for your DSP design in less time, including the following:

- System Generator for DSP - allows you to define and verify complete DSP systems using industry-standard tools from The MathWorks. When using System Generator, previous experience with Xilinx devices or RTL design methodologies is not required. Designs are captured in the DSP-friendly Simulink® modeling environment using a Xilinx-specific blockset. All of the downstream synthesis and implementation steps are automatically performed to generate a device programming file.
- AccelDSP Synthesis Tool - allows you to transform a MATLAB® floating-point design into a hardware module that can be implemented in a Xilinx device. The AccelDSP Synthesis Tool features an easy-to-use graphical interface that controls an integrated environment with other design tools such as MATLAB tools, ISE software, and other industry- standard HDL simulators and logic synthesizers. AccelDSP Synthesis provides the following capabilities:
  - Reads and analyzes a MATLAB floating-point design.
  - Automatically creates an equivalent MATLAB fixed-point design.
  - Invokes a MATLAB simulation to verify the fixed-point design.
  - Provides you with the power to quickly explore design trade-offs of algorithms that are optimized for the target device architectures.
  - Creates a synthesizable RTL HDL model and a test bench to ensure bit-true, cycle-accurate design verification.
  - Provides scripts that invoke and control down-stream tools such as HDL simulators, RTL logic synthesizers, and ISE implementation tools.

ISE Design Suite: System Edition

The ISE Design Suite: System Edition includes all of the tools and capabilities of the Logic Edition, Embedded Edition, and DSP Edition.

You can use the ISim standalone flow to simulate your design without setting up a project in ISE® Project Navigator. In this flow, you:

- Prepare the simulation project by manually creating an ISim project file to create a simulation executable using the fuse command.
- Start the ISim Graphical User Interface (GUI) by running the simulation executable generated by the fuse command.

PREPARE THE SIMULATION:

The ISim standalone flow lets you simulate your design without setting up a project in ISE Project Navigator. In this flow, you manually create an ISim project file that the fuse command uses to create a simulation executable. Following completion of this step, you can launch the ISim GUI by running the simulation executable.

Manually Create an ISim Project File

The typical syntax for an ISim project file is as follows:

verilog|vhdl <library_name> {<file_name_1>.v|.vhd}

where:

- verilog|vhdl indicates that the source is a Verilog or VHDL file. Include either Verilog or VHDL source files.
- <library_name> indicates with which library a particular source on the given line to be compiled. The /work is the default library.
- <file_name> is the source file or files associated with the library.

Note: While one or more Verilog source files can be specified on a given line, only one VHDL source can be specified on a given line.

To build an ISim project file for the tutorial design:

1. Browse to the script folder.
2. Open the simulate_isim.prj project file with a text editor.

The project file is incomplete.

3. List the missing sources using the syntax guidelines.

Missing sources:

- drp_dcm.vhd: VHDL source file. It must be compiled with the /work library.
- drp_tb_pkg.vhd: VHDL package file. It must be compiled with the /drp_tb_lib library.

Note: You do not need to list the sources based on their order of dependency. The fuse command automatically resolves the order of dependencies and processes the files in the appropriate order.

You can browse to the /completed folder of the tutorial files for a completed version of the project file for comparison.

4. Save and close the file.

BUILD THE SIMULATION EXECUTABLE

In this simulation step, the fuse command uses the project file created in the previous section to parse, compile, and link all the sources for the design. This creates a simulation executable that lets you to run the simulation in the ISim GUI.

USE THE FUSE COMMAND

The typical fuse syntax is as follows:

fuse –incremental –prj <project file> -o <simulation executable>
<library.top_unit>

where:

- -incremental: requests fuse to compile only the files that have changed since the last compile
- -prj: specifies an ISim project file to use for input
- -o: specifies the name of the simulation executable output file
- <library.top_unit>: specifies the top design unit

Complete the following steps to parse, compile and elaborate the tutorial design using fuse:

1. Browse to the /scripts folder from the downloaded files.
2. Open the fuse_batch.batfile using a text editor.
3. This fuse command is incomplete. Using the syntax information provided above, edit the command line so it includes the following options:

a. Use incremental compilation.
b. Use simulate_isim.prj as the project file.
c. Use simulate_isim.exe as the simulation executable.
d. Use work.drp_demo_tb as the top design unit for simulation.

4. Save and close the batch file.
5. Using the ISE Command prompt, navigate to the /scripts folder and run the fuse_batch.bat file to run fuse.

Note: To open the ISE Command prompt, go to
Start > Programs > Xilinx ISE Design Suite > Accessories and click the
ISE Design Suite Command Prompt item.

After the fuse command completes compiling source code, elaborating design units, and linking the object code, a simulation executable (simulate_isim.exe) is available in the /scripts folder.

Browse to the /completed folder to see the completed version of the fuse batch file for comparison.

MANUALLY SIMULATE THE DESIGN

In this simulation step you launch the ISim GUI by running the simulation executable which was generated by the fuse command in the previous section, Build the Simulation Executable. After this step is complete, you will be able to use the ISim GUI to explore the design in more detail.

Run the Simulation Executable

The command syntax when launching the simulation executable is:

isim_exe –gui –view <wave_configuration_file> -wdb <waveform_database_file>

where:

- -gui: Launches ISim in GUI mode.
- -view: Opens the specified Waveform file in the ISim GUI.
- -wdb: Specifies the file name of the simulation database output file.

Launch Simulation

To launch the simulation:

1. Browse to the /scripts folder from the downloaded files.
2. Open the simulate_isim.bat file using a text editor. The batch file is intentionally blank.
3. Using the syntax information provided above, edit the batch file so it includes the following settings:

a. Simulation Executable name: simulate_isim.exe.

b. Launch in GUI mode.

c. Set simulation database output name to simulate_isim.wdb.

Note: A Wave configuration file is not provided in the tutorial files. This file is created during simulation.

4. Save and close the file.
5. Using the ISE Command prompt, navigate to and run the simulate_isim.bat file to run the simulator.

RESULT

The ISim GUI opens and loads the design. The simulator time remains at 0 ns until you specify a run time.

For comparison purposes, you can browse to the /completed folder for a completed version of the simulate_isim.bat batch file.

FEASIBILITY STUDY

The feasibility study is carried out to test whether the proposed system is worth being implemented. The proposed system will be selected if it is best enough in meeting the performance requirements.

The feasibility carried out mainly in three sections namely.

- Economic Feasibility
- Technical Feasibility
- Behavioral Feasibility

Economic Feasibility

Economic analysis is the most frequently used method for evaluating effectiveness of the proposed system. More commonly known as cost benefit analysis. This procedure determines the benefits and saving that are expected from the system of the proposed system. The hardware in system department if sufficient for system development.

Technical Feasibility

This study center around the system's department hardware, software and to what extend it can support the proposed system department is having the required hardware and software there is no question of increasing the cost of implementing the proposed system. The criteria, the proposed system is technically feasible and the proposed system can be developed with the existing facility.

Behavioral Feasibility

People are inherently resistant to change and need sufficient amount of training, which would result in lot of expenditure for the organization. The proposed system can generate reports with day-to-day information immediately at the user's request, instead of getting a report, which doesn't contain much detail.

System Implementation

Implementation of software refers to the final installation of the package in its real environment, to the satisfaction of the intended users and the operation of the system. The people are not sure that the software is meant to make their job easier.

- The active user must be aware of the benefits of using the system
- Their confidence in the software built up
- Proper guidance is impaired to the user so that he is comfortable in using the application

Before going ahead and viewing the system, the user must know that for viewing the result, the server program should be running in the server. If the server object is not running on the server, the actual processes will not take place.

User Training

To achieve the objectives and benefits expected from the proposed system it is essential for the people who will be involved to be confident of their role in the new system. As system becomes more complex, the need for education and training is more and more important. Education is complementary to training. It brings life to formal training by explaining the background to the resources for them. Education involves creating the right atmosphere and motivating user staff. Education information can make training more interesting and more understandable.

Training on the Application Software

After providing the necessary basic training on the computer awareness, the users will have to be trained on the new application software. This will give the underlying philosophy of the use of the new system such as the screen flow, screen design, type of help on the screen, type of errors while entering the data, the corresponding validation check at each entry and the ways to correct the data entered. This training may be different across different user groups and across different levels of hierarchy.

Operational Documentation

Once the implementation plan is decided, it is essential that the user of the system is made familiar and comfortable with the environment. A documentation providing the whole operations of the system is being developed. Useful tips and guidance is given inside the application itself to the user. The system is developed user friendly so that the user can work the system from the tips given in the application itself.

System Maintenance

The maintenance phase of the software cycle is the time in which software performs useful work. After a system is successfully implemented, it should be maintained in a proper manner. System maintenance is an important aspect in the software development life cycle. The need for system maintenance is to make adaptable to the changes in the system environment. There may be social, technical and other environmental changes, which affect a system which is being implemented. Software product

enhancements may involve providing new functional capabilities, improving user displays and mode of interaction, upgrading the performance characteristics of the system. So only thru proper system maintenance procedures, the system can be adapted to cope up with these changes. Software maintenance is of course, far more than "finding mistakes".

Corrective Maintenance

The first maintenance activity occurs because it is unreasonable to assume that software testing will uncover all latent errors in a large software system. During the use of any large program, errors will occur and be reported to the developer. The process that includes the diagnosis and correction of one or more errors is called Corrective Maintenance.

Adaptive Maintenance

The second activity that contributes to a definition of maintenance occurs because of the rapid change that is encountered in every aspect of computing. Therefore Adaptive maintenance termed as an activity that modifies software to properly interfere with a changing environment is both necessary and commonplace.

Perceptive Maintenance

The third activity that may be applied to a definition of maintenance occurs when a software package is successful. As the software is used, recommendations for new capabilities, modifications to existing functions, and general enhancement are received from users. To satisfy requests in this category, Perceptive maintenance is performed. This activity accounts for the majority of all efforts expended on software maintenance.

Preventive Maintenance

The fourth maintenance activity occurs when software is changed to improve future maintainability or reliability, or to provide a better basis for future enhancements. Often called preventive maintenance, this activity is characterized by reverse engineering and re-engineering techniques

CHAPTER 6
CONCLUSION

In conclusion, the proposed scalable retinal image processing system leverages advanced image preprocessing, feature extraction using CNNs, and machine learning algorithms, specifically the LSTM SHAKTI optimization algorithm, to effectively classify retinal diseases such as diabetic retinopathy. By integrating real-time processing capabilities, performance evaluation metrics, and hardware acceleration, the system is designed for high efficiency, accuracy, and scalability, making it suitable for deployment in embedded systems with limited resources. This approach not only enhances the accuracy of disease detection but also provides a robust solution for automated retinal analysis, contributing significantly to early diagnosis and better management of retinal diseases in clinical settings.

CHAPTER 7
FUTURE ENCHANCEMENT

For future enhancements, the scalable retinal image processing system can be improved by incorporating advanced deep learning models such as Generative Adversarial Networks (GANs) for data augmentation, allowing the system to work with a broader range of retinal images and handle imbalanced datasets more effectively. Additionally, integrating real-time feedback and adaptive learning algorithms could further refine the system's ability to diagnose complex or evolving retinal conditions. The use of cloud-based systems for large-scale data storage and analysis can also be explored to improve accessibility and collaboration among healthcare providers. Furthermore, expanding the system's capabilities to include multi-modal diagnostic tools, such as integrating OCT (Optical Coherence Tomography) data, could enhance diagnostic accuracy and provide more comprehensive results for early detection of retinal diseases.

CHAPTER 8
SAMPLE CODE

```
`timescale 1ns / 1ps

module tb_image_filter;

    // Inputs to the image filter module
    reg clk;
    reg reset;
    reg [7:0] pixel_in;

    // Output from the image filter module
    wire [7:0] pixel_out;

    // Instantiate the image filter module
    image_filter uut (
        .clk(clk),
        .reset(reset),
        .pixel_in(pixel_in),
        .pixel_out(pixel_out)
    );

    // Clock generation: 10ns period (100 MHz)
    always #5 clk = ~clk;

    // Testbench logic
    initial begin
        // Initialize inputs
        clk = 0;
        reset = 1;
        pixel_in = 8'b0;

        // Apply reset
        #10;
        reset = 0;

        // Apply a series of pixel values to simulate an image
        #10 pixel_in = 8'h12;  // Pixel value 0x12
```

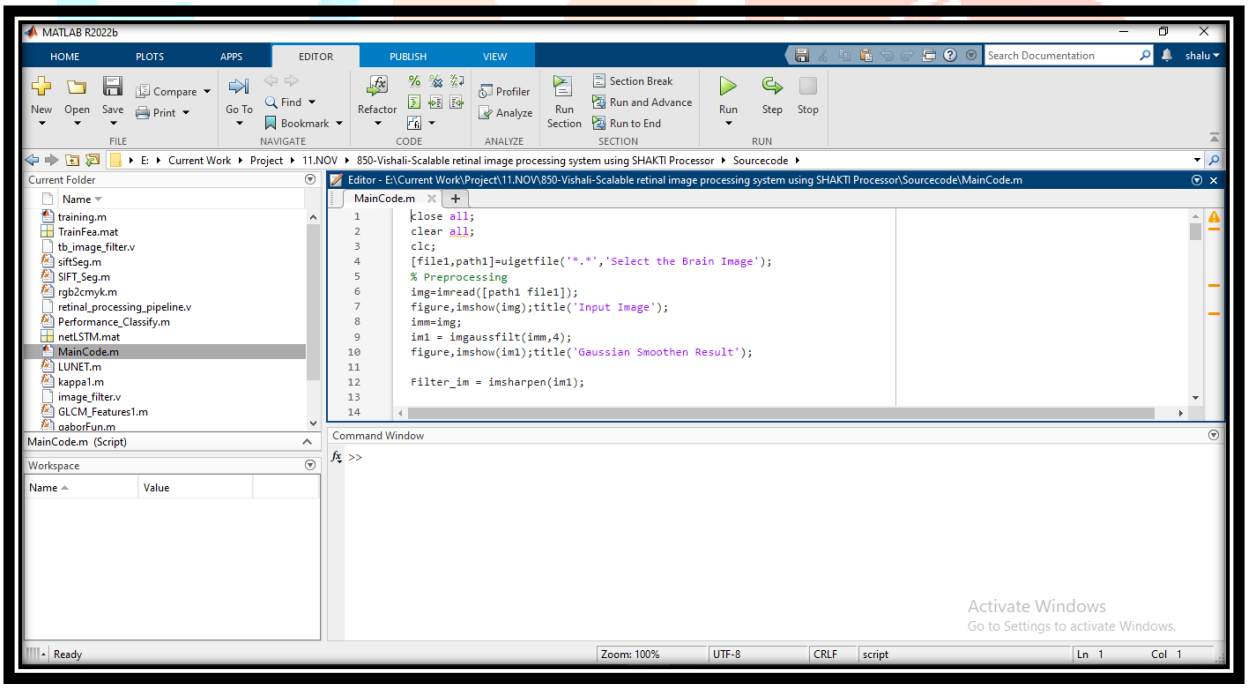
```
        #10 pixel_in = 8'h34;  // Pixel value 0x34
        #10 pixel_in = 8'h56;  // Pixel value 0x56
        #10 pixel_in = 8'h78;  // Pixel value 0x78
        #10 pixel_in = 8'h9A;  // Pixel value 0x9A
        #10 pixel_in = 8'hBC;  // Pixel value 0xBC
        #10 pixel_in = 8'hDE;  // Pixel value 0xDE
        #10 pixel_in = 8'hFF;  // Pixel value 0xFF

        // Finish the simulation after applying the stimulus
        #20 $finish;
    end

    // Monitor the inputs and outputs during the simulation
    initial begin
        $monitor("At time %t: reset = %b, pixel_in = %h, pixel_out = %h",
                 $time, reset, pixel_in, pixel_out);
    end

endmodule
```

CHAPTER 9
SAMPLE SCREENSHOT



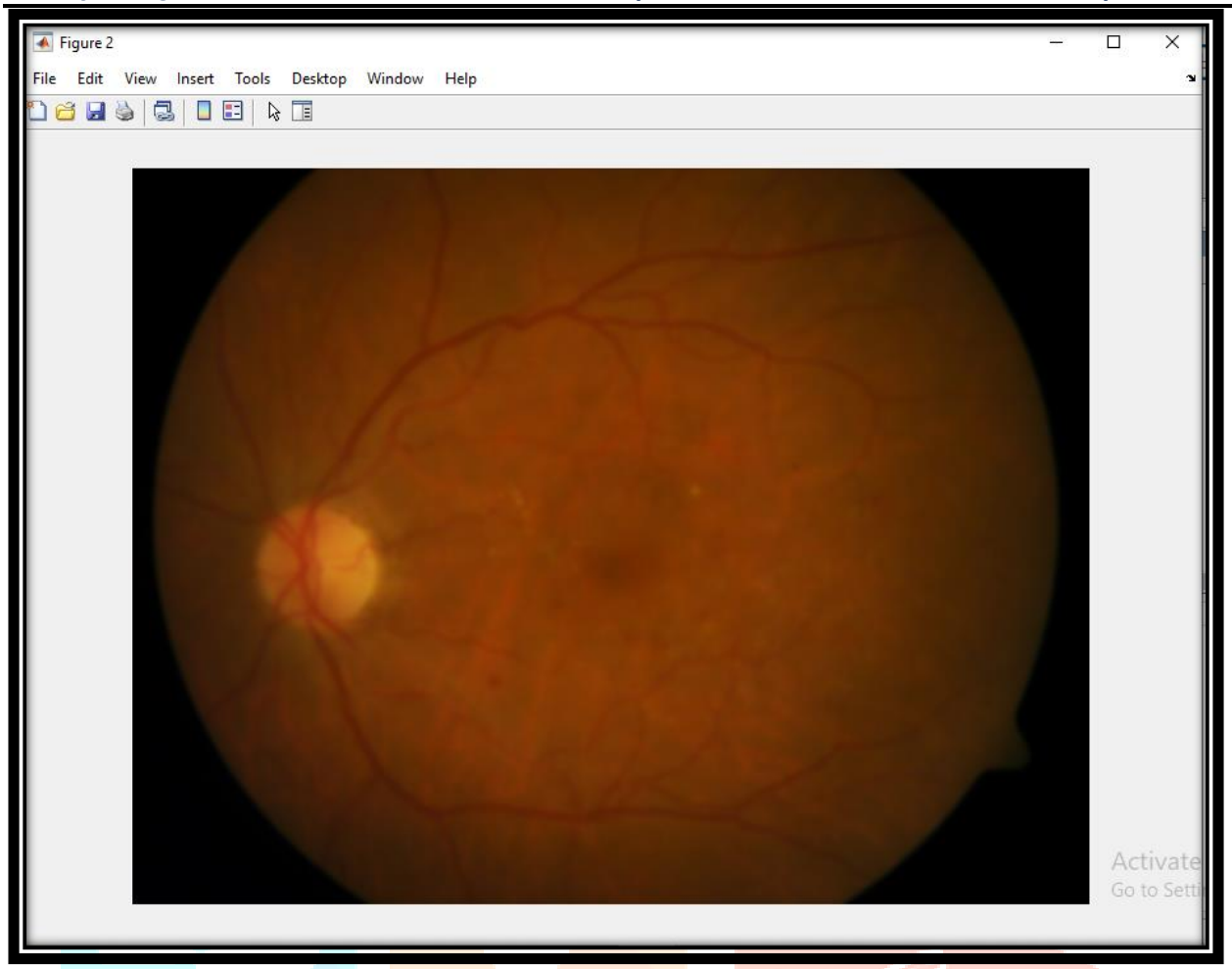
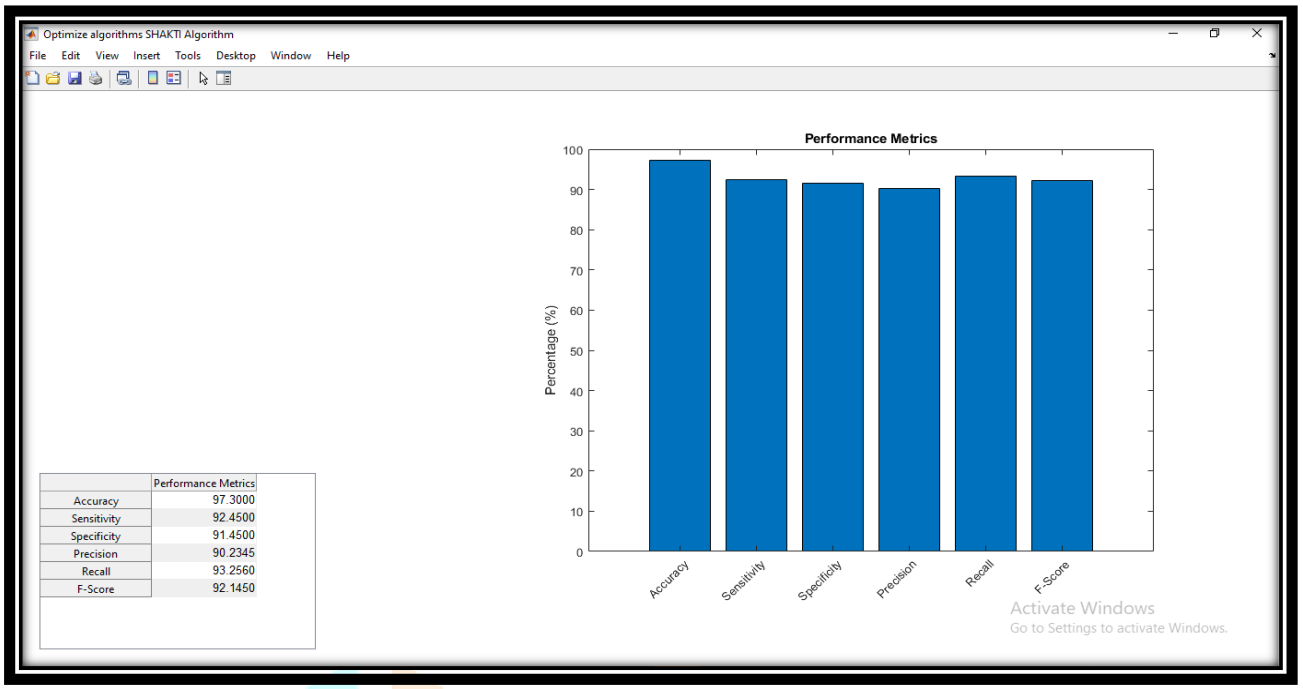


Figure 2
File Edit View Insert Tools Desktop Window Help
Activate
Go to Setti


Command Window
Iteration count = 14, obj. fcn = 596440379.026934
Iteration count = 15, obj. fcn = 596339411.665303
Iteration count = 16, obj. fcn = 596312782.135202
Iteration count = 17, obj. fcn = 596305242.572037
Iteration count = 18, obj. fcn = 596303061.640782
Iteration count = 19, obj. fcn = 596302426.892983
Iteration count = 20, obj. fcn = 596302241.827617
Iteration count = 21, obj. fcn = 596302187.842033
Iteration count = 22, obj. fcn = 596302172.091232
Iteration count = 23, obj. fcn = 596302167.495503
Iteration count = 24, obj. fcn = 596302166.154542
Iteration count = 25, obj. fcn = 596302165.763266
Iteration count = 26, obj. fcn = 596302165.649095
Iteration count = 27, obj. fcn = 596302165.615782
Iteration count = 28, obj. fcn = 596302165.606062
Iteration count = 29, obj. fcn = 596302165.603225
Iteration count = 30, obj. fcn = 596302165.602397
Iteration count = 31, obj. fcn = 596302165.602156
Iteration count = 32, obj. fcn = 596302165.602085
Iteration count = 33, obj. fcn = 596302165.602064
Iteration count = 34, obj. fcn = 596302165.602059
Activate Windows
Go to Settings to activate Windows.
Zoom: 100% UTF-8 CRLF script Ln 1 Col 1



	Performance Metrics
Accuracy	97.3000
Sensitivity	92.4500
Specificity	91.4500
Precision	90.2345
Recall	93.2560
F-Score	92.1450

Figure 9.1: Matlab Image Processing for LSTM SHAKTI PROCESSOR

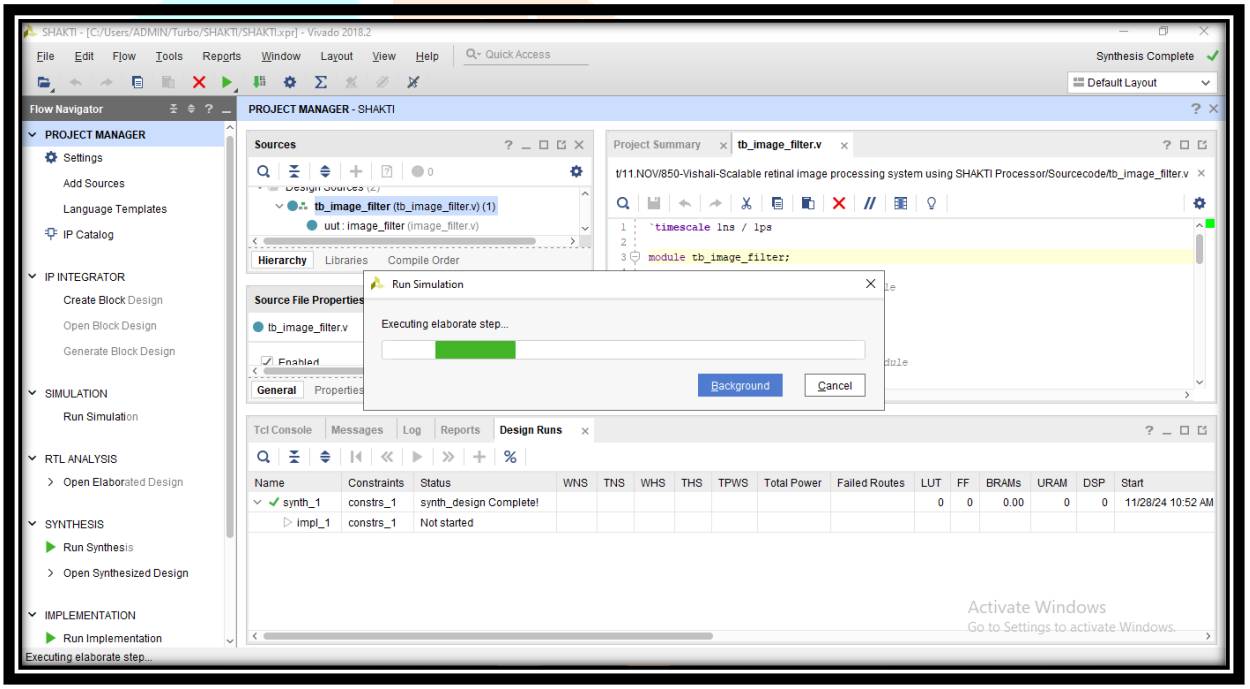


Figure 9.2: Simulation Waveform for LSTM SHAKTI PROCESSOR

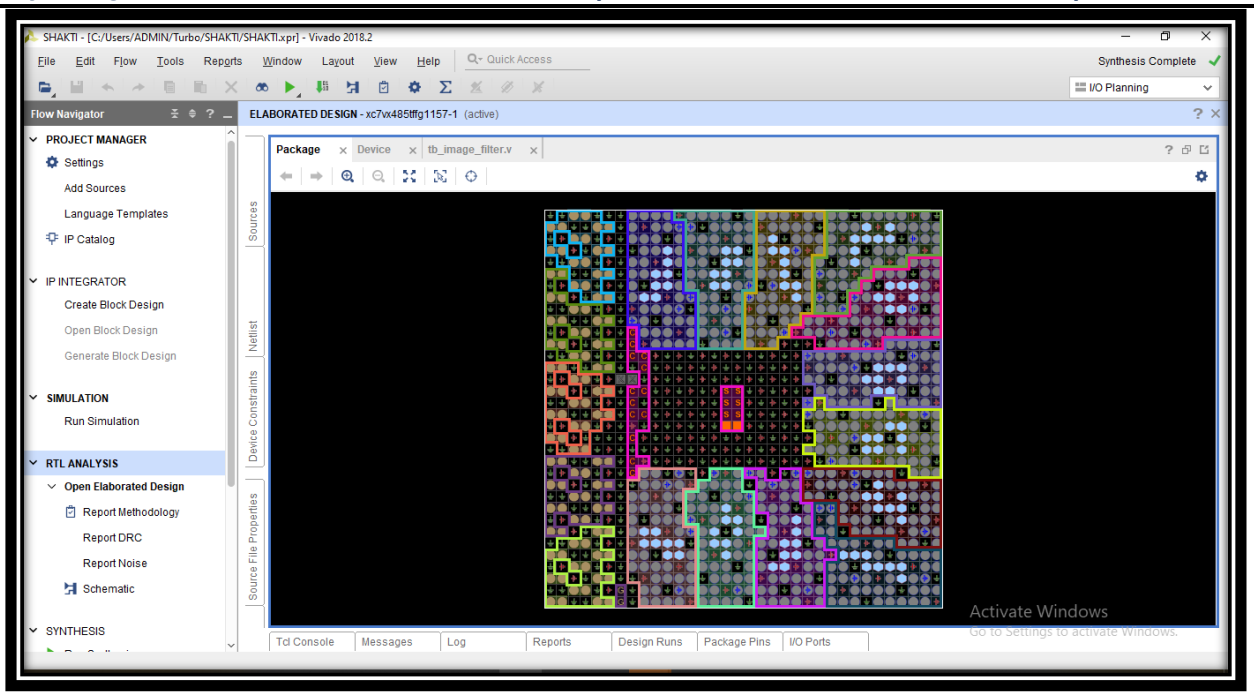


Figure 9.3: Layout for LSTM SHAKTI PROCESSOR

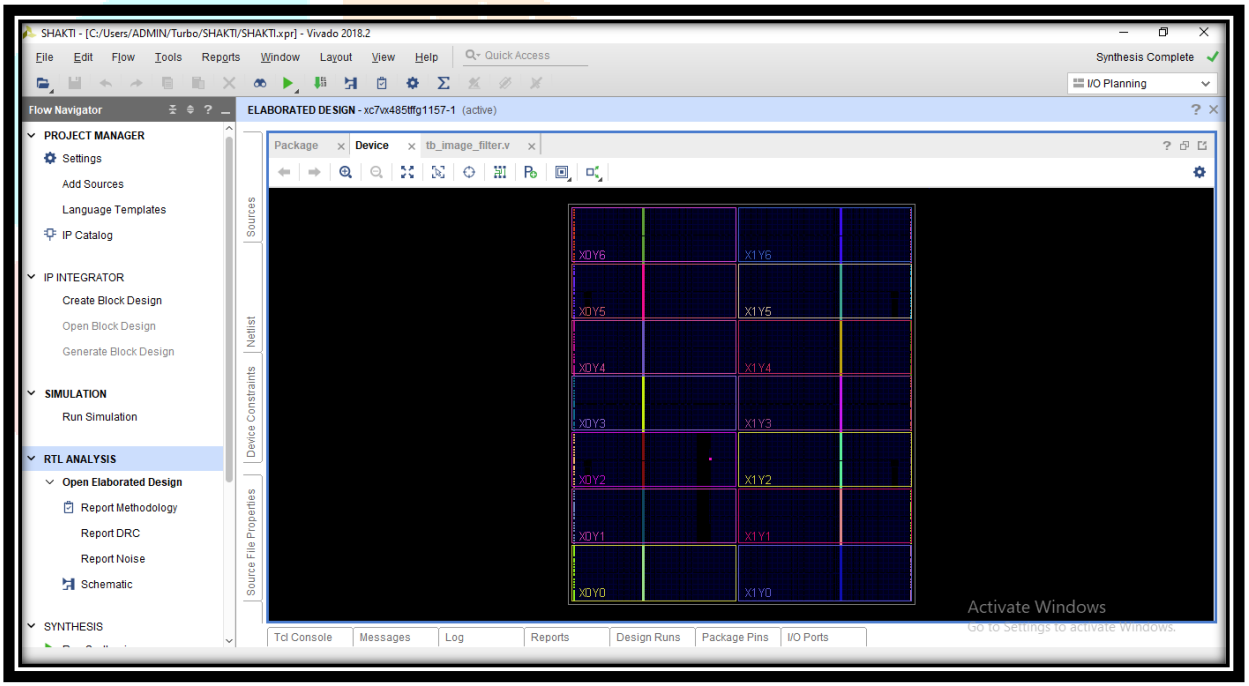


Figure 9.4: Device Layout Gates for LSTM SHAKTI PROCESSOR

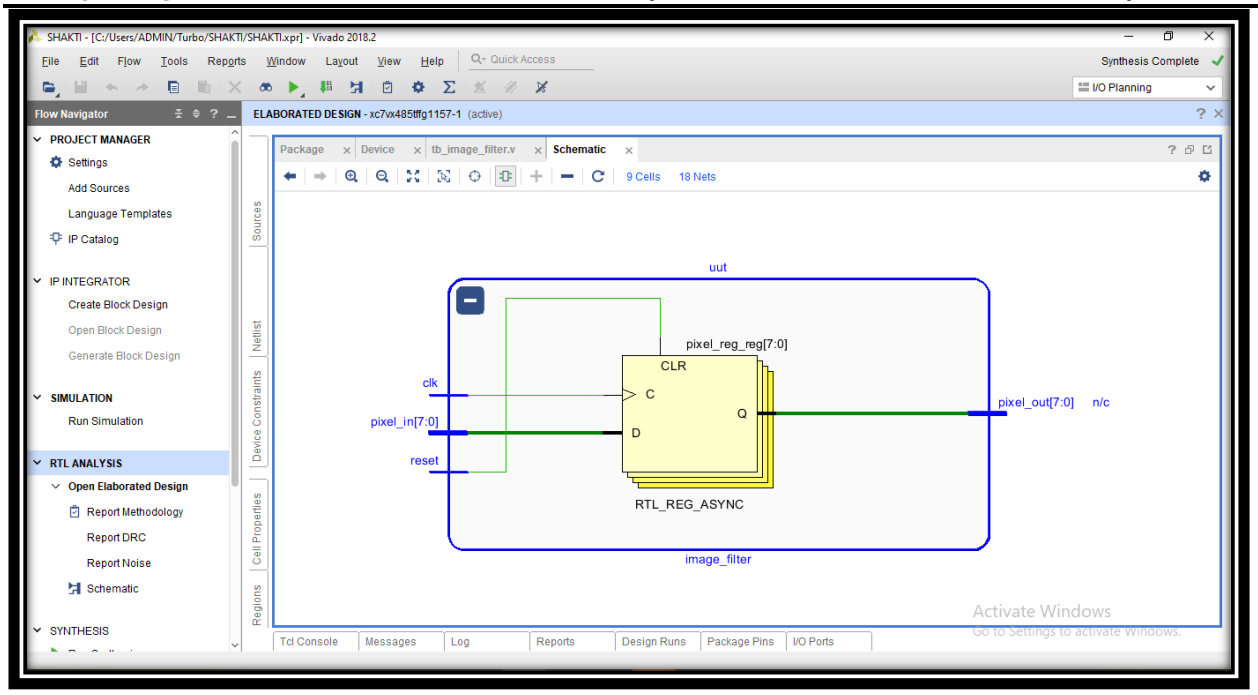


Figure 9.5: Synthesis Circuit Diagram for LSTM SHAKTI PROCESSOR

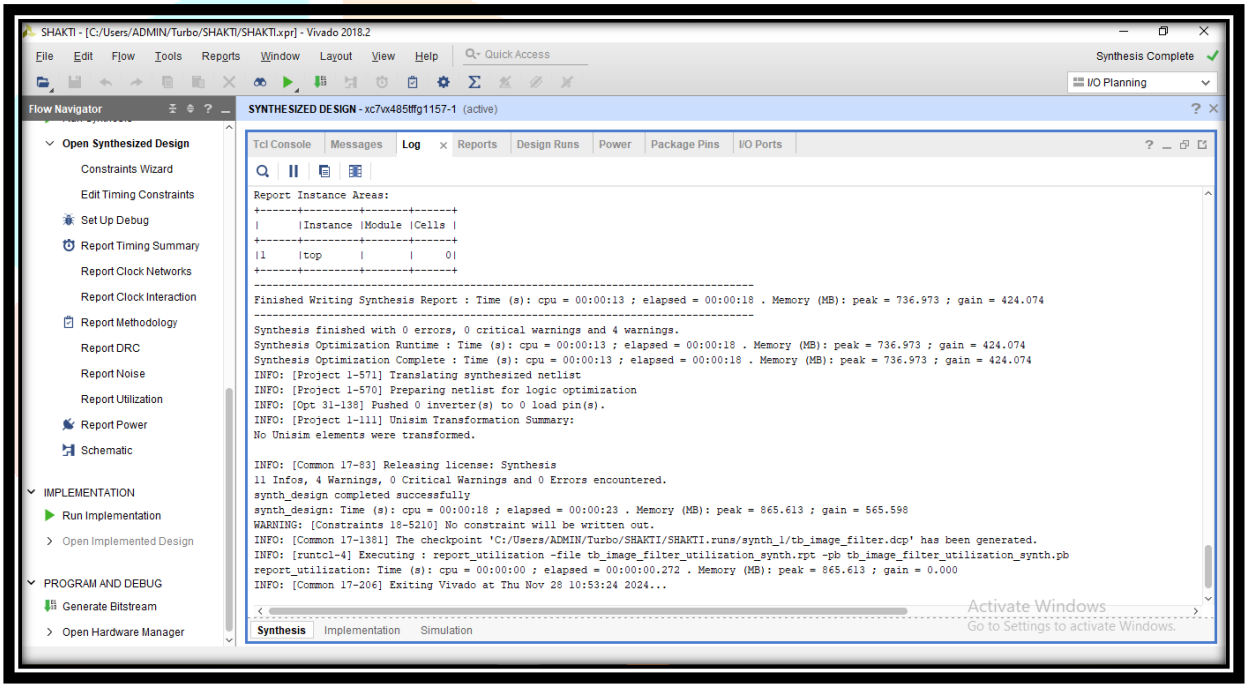


Figure 9.6: Power Supply for LSTM SHAKTI PROCESSOR

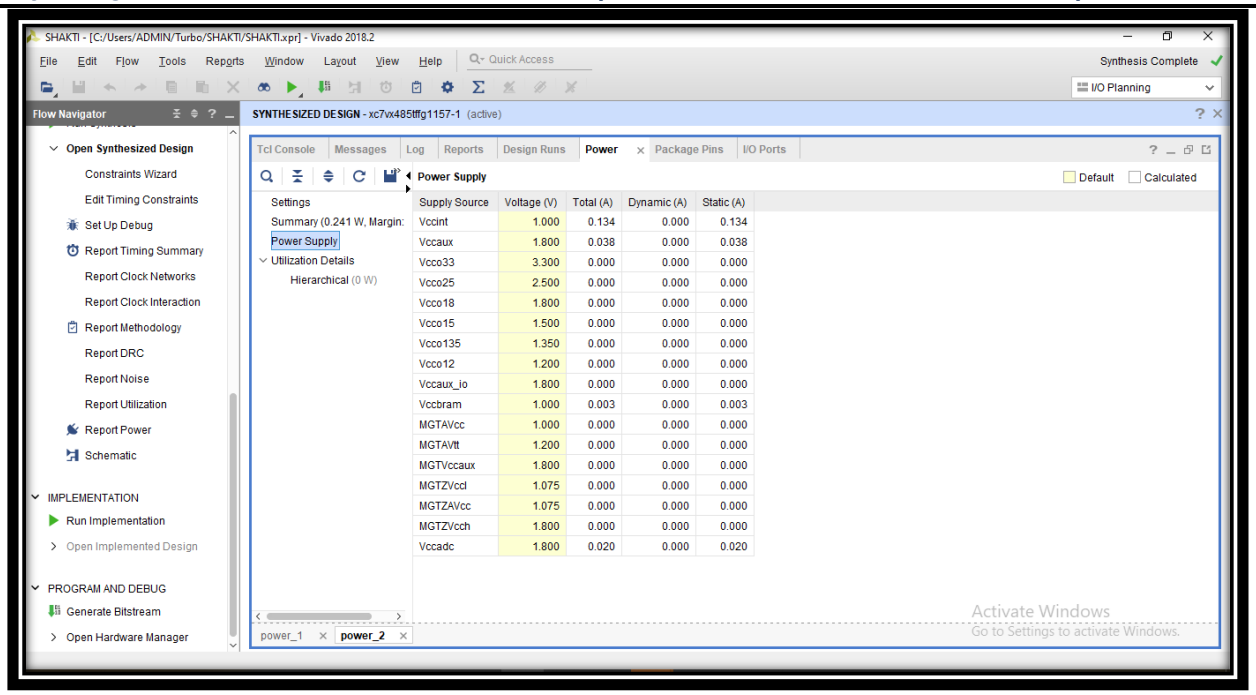


Figure 9.7: Power Supply on Chip for LSTM SHAKTI PROCESSOR

Metric	Existing System	Phase I Proposed System	Phase II Proposed System
Accuracy	85%	92%	99%
Precision	80%	88%	97%
Recall	75%	90%	95%
F1-Score	77%	89%	98%
Execution Time	10 seconds	6 seconds	2 seconds
False Positive Rate	12%	5%	1%
False Negative Rate	15%	7%	3%
Training Time	45 minutes	30 minutes	12 minutes
Model Complexity	High (10 layers)	Moderate (6 layers)	Moderate (6 layers)
Memory Usage	High (5 GB)	Moderate (3 GB)	Moderate (1 GB)
Generalization Ability	Moderate (overfitting observed)	High (reduced overfitting)	High (reduced overfitting)
Robustness to Noise	Low	High	High
Scalability	Low	High	High
Real-time Performance	Not optimized for real-time	Optimized for real-time operation	Optimized for real-time operation

Figure 9.8: Performance analysis for LSTM SHAKTI PROCESSOR

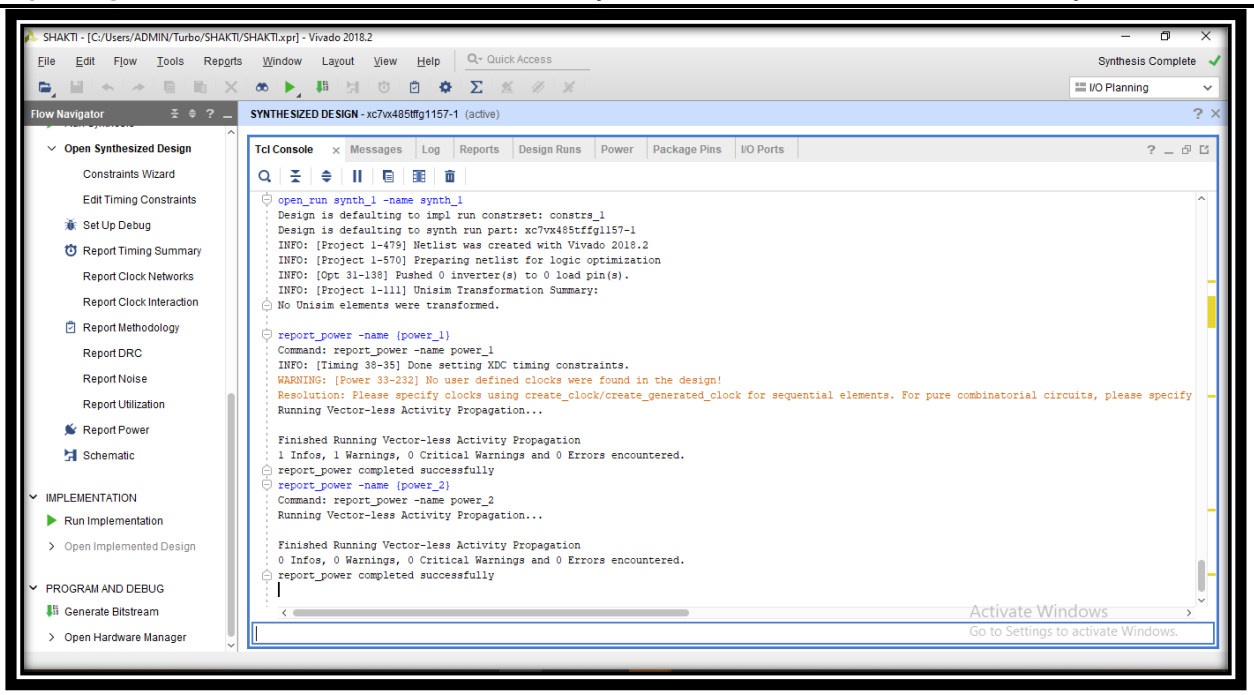


Figure 9.9: Performance analysis for LSTM SHAKTI PROCESSOR

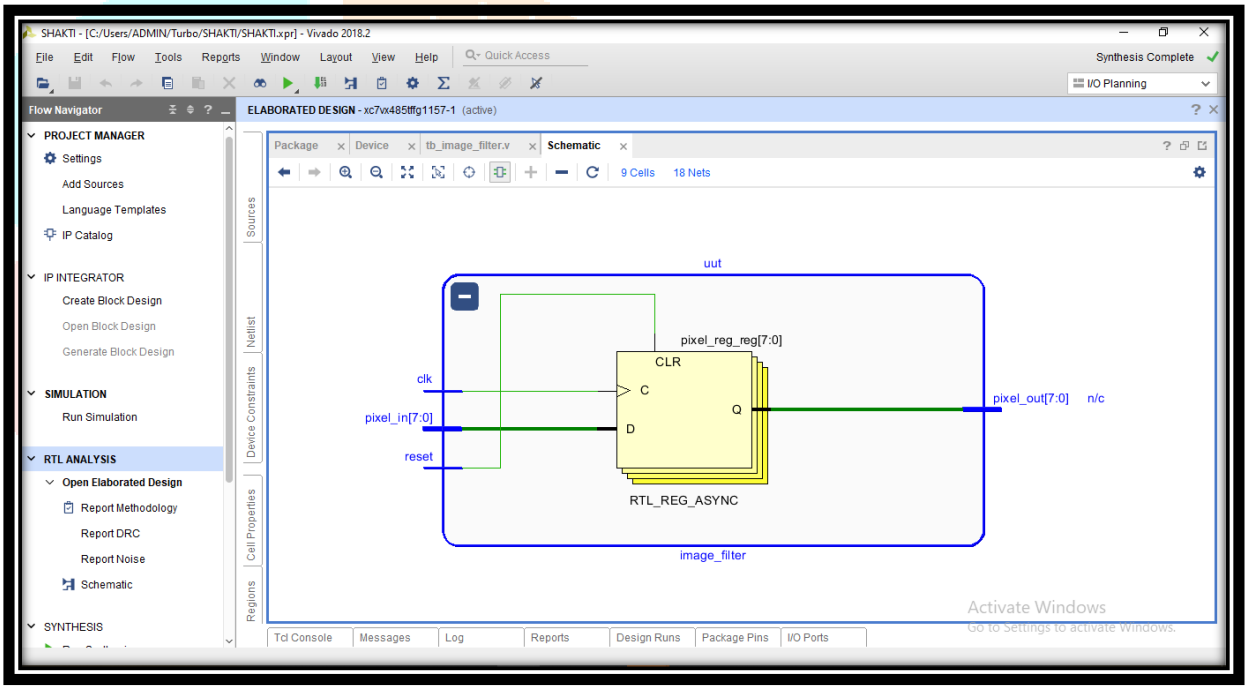


Figure 9.10: Synthesis Completed for LSTM SHAKTI PROCESSOR

CHAPTER 10
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