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FPGA-based automatic Pill Dispenser using Decision Tree Classifier

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ABSTRACT

The proposed method involves the classification of Pills and dispenses at the required time to the elderly persons and patients. The decision tree machine learning methodology is included for the classification of Pills based on features namely color, shape, and size. The main objective of this proposed method is to help elderly people and patients in dispensing accurate pills in the prescribed time. Though there are several machine algorithms are used for classification, the Decision Tree algorithm classifies the features with high accuracy and can handle complex datasets. In this work, the Decision Tree algorithm is developed for the given sample dataset of the pill dispensed based on the time. The developed decision tree-based classification is HDL coded and verified with the real-time Xilinx Artix-7 FPGA device. The performance analysis of the proposed method is evaluated for power and area using the EDA tools.

Keywords: *Pill Separator, Decision Tree Algorithm, Hardware Description Language, Field Programmable Gate Array*

INTRODUCTION

Medical care for elderly people and patients is challenging in many countries across the globe. Many times, the fatality rate is increasing due to medical and treatment errors. The most common issue in treatment error is the inability of the patient and elder people to recognize the pills based on the time of consumption. The presented medical error demands a more accurate methodology to assuring the correct pills are delivered to the patients and elderly persons at the prescribed time.

In most cases of pill consumption treatment error, elderly persons and patients are unable to recognize the pill's features such as color, shape, size, type, and time of consumption. This requires excess monitoring of the patients especially those with chronic diseases in the hospitals and at home. Several methods have been proposed in the past, but the advent of Machine Learning and Deep Learning algorithms paid the way for the efficient and accurate classification of pills based on the person's demand. To avoid medical errors, the mobile application is developed to discharge the dosage of the pills based on the weight and age of the patients [1]. The automated pill recognition system based on a deep learning algorithm increases the data annotation cost [2]. The detection of different pills and their combinations in image exponentially increases and leads to a loss of productivity in dispensing pills [3].

Also, the purpose of the machine and deep learning become pivotal for specific diseases in the world. The utilization of Machine learning algorithms proves to be advantageous in the early detection of Parkinson's disease for old aged people [4]. The MedGlasses system benefits visually impaired people to take correct and safe drugs [5]. The Markov-Chain Monte-Carlo (MCMC) algorithm is used as a compensatory method for machine learning to detect the seizure in the brain [6].

Further, deep learning algorithms are designated to aid in precise medical and clinical treatment. The sustained evolution of the deep learning algorithm is used in the development of surveys and formulation of novel products in the field of biomedical research. Deep learning algorithms are utilized in several stages of medicine development since 2000 [7]. The advent of multi-model dataset usage can enhance the prediction in clinical decision support [8]. Though there are several machine learning algorithms for classification, the decision tree algorithm is best suited for accurate classification and the capability to handle large datasets in classification. The evolution of decision tree algorithms for image classification is prominent in many applications such as space, remote sensing, underwater monitoring, crop and seed classification for farming, and health care monitoring.

To validate the real-time implementation of the machine and deep learning algorithm for medical and clinical care, the FPGA digital control is suitable for its low power consumption, parallel processing, reconfigurable property, easy debugging, and portable. Recently, the FPGA device is used in the precise monitoring of specific health issues such as asthma, cancer, and visually impaired patients. The wheezing recognition system is developed using the Xilinx Virtex-6 FPGA device to extract the features of wheezing using a spectrogram [9].

Apart from health care monitoring, the FPGA fusion with the decision tree is utilized in different real-time classifications and detection of errors. The FPGA implementation of the Decision Tree Algorithm consumes low power when the size of the dataset increases [10]. The use of two means lower complexity Decision Tree algorithm can exhibit low power and high performance with FPGA implementation [11]. The Optimized Decision Tree algorithm uses the divide and conquers method to classify the traffics in the transport layer of the networks [12]. The faults in the switching of the inverters are classified using the modified decision tree algorithm [13]. The SOC-based FPGA architecture design makes use of the Quickscorer for high performance and accurate inference tasks in decision tree [14]. In this work, the pills are classified using the decision tree algorithm and implemented in an FPGA device. Also, the IC layout is presented for the developed Decision tree algorithm-based pill separator and dispenser. Section-II discusses the proposed pill dispenser using the Decision tree algorithm, and Section-III depicts the results and discusses the outcome of the proposed method. Section IV concludes the proposed pill dispenser.

The Proposed Work: Decision Tree Algorithm For Pill Classification Using FPGA

The proposed automatic pill dispenser for elder and disabled persons helps in the separation of pills based on color, shape, and size; and automatically dispenses in the specified time. The decision tree machine learning algorithm is utilized in the classification of the pills according to the timing of dispense. For the evaluation, the data set is developed for the pill separation considering the three main features namely color, shape, and size with the decision of timing as a predicted outcome. The design flow for the proposed method is depicted in Figure 1. The features for the proposed pill separator are digitized and represented using 5 bits of data namely F4, F3, F2, F1, and F0. As given in Figure 2, the Least Significant Bit (F0) presents the size of the pill, the next two bits namely F2, F1 are utilized for the shape of the pill, and the F4,F3 bits are used to represent the color of the pill. When the 5-bit data is fed, the bits are split as per the features of the proposed pill separator.

The binarized pills dataset is developed and customized according to the proposed method for the sake of real-time validation. Table 1 depicts the pill separator dataset samples for the decision of timings in the dispense of medicine. Here, 22 samples along with the features are considered for the development of the Decision Tree Algorithm. The three features are labeled as Color, Shape, and Size for the given sample dataset. Further, the color features consist of 4 attributes namely Blue, Red, Orange, and Green. For the feature of shape, there are 3 attributes represented Rectangular, Cylindrical, and Circular; for the size, there are 2 attributes given as Small and Medium. The timing of medicine dispense depends on these combinations of features along with their attributes as presented in Table 1.

Considering the Table 1 dataset, the decision tree algorithm is derived using the entropy and Information gain calculation for the features and the attributes. Initially, the entropy of the overall dataset is manipulated based on the decision for the times of medicine dispenses namely “Morning” and “Night”. Among the 22 samples, there are 10 medicines to be dispensed in the “Morning” and 12 medicines to be dispensed in the “Night”. Then the entropy is calculated for the individual attributes of each feature to derive the Information gain of the features. The decision tree for the proposed pill separator is derived using the entropy and information gain formula.The entropy is manipulated for the proposed method for the three features namely color, shape, and size. The formulation for the entropy for the Color is given by (1).

$$COLOR_{TOTAL} = -\frac{10}{22}log_2\left(\frac{10}{22}\right) - \frac{12}{22}log_2\left(\frac{12}{22}\right) \quad (1)$$

Similarly, the entropy for the red, blue, green, and orange within the Color is depicted in (2) to (5) respectively.

$$COLOR_{(RED)} = -\frac{3}{7}log_2\left(\frac{3}{7}\right) - \frac{4}{7}log_2\left(\frac{4}{7}\right) \quad (2)$$

$$COLOR_{(BLUE)} = -\frac{4}{5}log_2\left(\frac{4}{5}\right) - \frac{1}{5}log_2\left(\frac{1}{5}\right) \quad (3)$$

$$COLOR_{(GREEN)} = -\frac{2}{6}log_2\left(\frac{2}{6}\right) - \frac{4}{6}log_2\left(\frac{4}{6}\right) \quad (4)$$

$$COLOR_{(ORANGE)} = -\frac{1}{4}log_2\left(\frac{1}{4}\right) - \frac{3}{4}log_2\left(\frac{3}{4}\right) \quad (5)$$

The gain of the Color is given by the formulation in (6),

$$Gain(color) = Entropy\ of\ Color - \frac{7}{22}(Entropy\ of\ Red) - \frac{5}{22}(Entropy\ of\ Blue) - \frac{6}{22}(Entropy\ of\ Green) - \frac{4}{22}(Entropy\ of\ Orange) \quad (6)$$

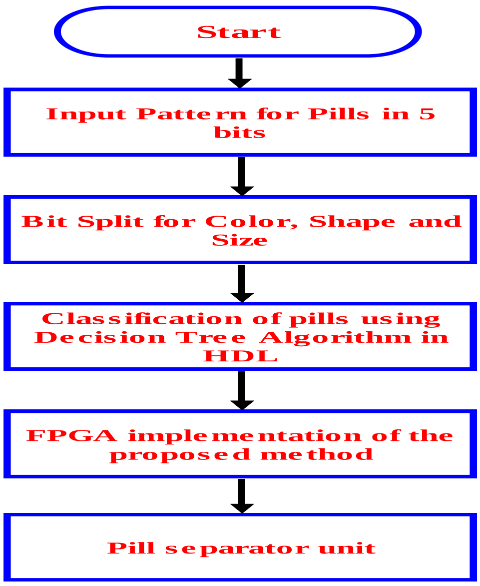


FIGURE 1: FPGA based Design flow for the proposed Pill separator

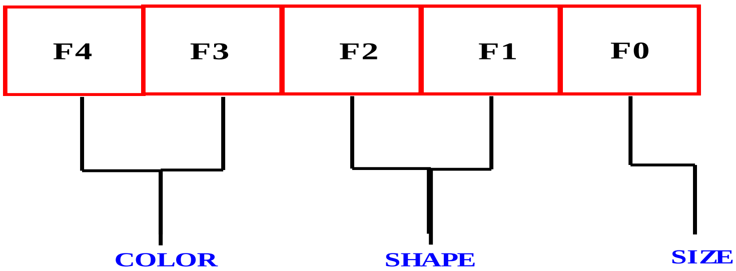


FIGURE 2: Features of Pill separator represented in 5 bit data format

TABLE 1: Sample Dataset for the proposed Pill dispenser

Sl. No.	Color	Shape	Size	Time
1	Blue	Circular	Medium	Morning
2	Red	Circular	Small	Morning
3	Green	Rectangular	Medium	Night
4	Orange	Circular	Medium	Morning
5	Red	Rectangular	Small	Night
6	Blue	Rectangular	Medium	Morning
7	Green	Circular	Small	Night
8	Blue	Cylindrical	Small	Morning
9	Orange	Cylindrical	Medium	Night
10	Green	Cylindrical	Medium	Night
11	Green	Rectangular	Small	Morning
12	Red	Cylindrical	Small	Morning
13	Blue	Cylindrical	Medium	Night
14	Orange	Circular	Small	Night
15	Red	Rectangular	Medium	Night
16	Red	Circular	Medium	Night
17	Green	Circular	Medium	Morning
18	Orange	Rectangular	Small	Night
19	Red	Rectangular	Small	Morning
20	Blue	Rectangular	Small	Morning
21	Red	Cylindrical	Medium	Night
22	Green	Cylindrical	Small	Night

The calculation of Entropy and Gain for the Shape is evaluated as depicted in (7).

$$SHAPE_{TOTAL} = -\frac{10}{22}log_2\left(\frac{10}{22}\right) - \frac{12}{22}log_2\left(\frac{12}{22}\right) \quad (7)$$

Similarly, the entropy for the circular, cylindrical, and rectangular shape is depicted in (8) to (10) respectively.

$$SHAPE_{(CIRCULAR)} = -\frac{4}{7}log_2\left(\frac{4}{7}\right) - \frac{3}{7}log_2\left(\frac{3}{7}\right) \quad (8)$$

$$SHAPE_{(CYLINDER)} = -\frac{2}{7}log_2\left(\frac{2}{7}\right) - \frac{5}{7}log_2\left(\frac{5}{7}\right) \quad (9)$$

$$SHAPE_{(RECTANGULAR)} = -\frac{4}{8}log_2\left(\frac{4}{8}\right) - \frac{4}{8}log_2\left(\frac{4}{8}\right) \quad (10)$$

The gain of the Shape is given by the formulation of (11).

$$Gain(Shape) = Entropy\ of\ Shape - \frac{7}{22}(Entropy\ of\ Circular) - \frac{7}{22}(Entropy\ of\ Cylinder) - \frac{8}{22}(Entropy\ of\ Rectangular) \quad (11)$$

The calculation of Entropy and Gain for the Size is evaluated as depicted in (12).

$$SIZE_{TOTAL} = -\frac{10}{22}log_2\left(\frac{10}{22}\right) - \frac{12}{22}log_2\left(\frac{12}{22}\right) \quad (12)$$

Similarly, the entropy for the small and medium in the size is depicted in (13) and (14) respectively.

$$SIZE_{(SMALL)} = -\frac{4}{11}log_2\left(\frac{4}{11}\right) - \frac{7}{11}log_2\left(\frac{7}{11}\right) \quad (13)$$

$$SIZE_{(MEDIUM)} = -\frac{6}{11}log_2\left(\frac{6}{11}\right) - \frac{5}{11}log_2\left(\frac{5}{11}\right) \quad (14)$$

The gain of the Color is given by the formulation in (15)

$$Gain(Size) = Entropy\ of\ Size - \frac{11}{22}(Entropy\ of\ Small) - \frac{11}{22}(Entropy\ of\ Medium) \quad (15)$$

Table 2 presents the evaluated entropy values for the features and their attributes by taking into account the equations as given from (1) to (15). Table 3 depicts the Information Gain values for the features of the proposed pill dispenser and indicates that the Color has the maximum value to be considered as the Root node for the decision tree. Within the color feature, the hierarchy of attributes is selected based on the increasing values of the entropies as given in Table 2. For the Color feature, the orientation is Red, Green, Orange, and Blue. Similarly, the next highest information gain value in Table 3 is the shape feature, their attribute ordering is taken from Table 2 as Cylindrical, Circular, and Rectangular. Finally, the feature of size is considered with its attributes of Small followed by Medium

TABLE 2: Entropy Calculation for the attributes of the features in the proposed pill dispenser

Features of the Pills with the Entropy calculation for the given dataset					
Color	Entropy	Shape	Entropy	Size	Entropy
Red	0.98526	Circular	0.98525711	Small	0.994045
Blue	0.72192	Rectangular	0.86311429	Medium	0.945664
Green	0.91833	Cylindrical	1.0		
Orange	0.81125				

TABLE 3: Information Gain calculation for the features of the proposed Pill Dispenser

Features of the Pills	Information Gain
Color	0.118528
Shape	0.042291
Size	0.024191

By using the information gains of each attribute, the decision node is developed as shown in Figure 3. The Color feature with high information gain becomes the Decision node or Root node. Then the remaining features are considered for the branches of the decision node. The number of branches is equal to the number of possibilities of the features. Table 4 depicts the detailed feature representation for the proposed pill separator in the 5 bits. The value of the color feature in 2 bits is derived from the entropy and information gain values given in Table 2 and Table 3 to represent the "00" for Red; "01" for Green; "10" for Orange and "11" for Blue. Similarly, for the shape feature, the 2 bits are assigned as "00" for cylindrical, "01" for Circular, and "10" for Rectangular with the unassigned value for "11" as there are only 3 attributes. Also, the size feature of the pill has the possible value of ‘0’ for the small size and ‘1’ for the medium size. The outcome of the pill dispenser for the given sample data set is depicted in the form of the decision tree in Figure 3. The decision tree algorithm for the proposed pill classifier has the orientation of Color, Shape, and Size from the root node to the leaf node to decide whether the pill has to be delivered in the Morning or Night.

TABLE 4: Features of the Pills represented in binary format for 5-bit resolution

Color	Binary Value (2-bits)	Shape	Binary Value (2-bits)	Size	Binary Value (1-bit)
Red	00	Cylindrical	00	Small	0
Green	01	Circular	01	Medium	1
Orange	10	Rectangular	10		
Blue	11	Unassigned	11		

Based on the 5-bit data, the pill data set is given as input for the HDL-based Decision tree algorithm. The derived decision tree is utilized in the development of the HDL code for the proposed pill separator and dispenser. The decision tree HDL code is developed using the nested IF-Else statement in the behavioral modeling. The 5 bits of inputs are bit split and fed as input for the decision tree HDL code using the structural modeling. The HDL code for the proposed method is simulated and synthesized using the cadence tools. For the real-time validation, the proposed pill dispenser is implemented using the FPGA board and verified using the prototype.

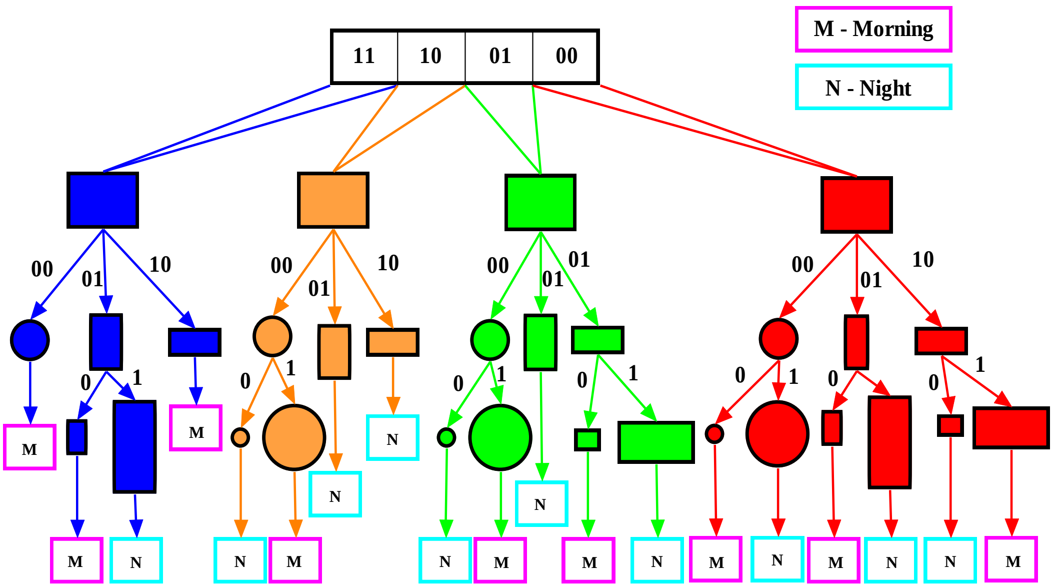


FIGURE 3: Tree diagram for the proposed Pill Dispenser using the Decision Tree Algorithm

RESULTS AND DISCUSSION

The proposed FPGA-based pill separator using the Decision tree algorithm is developed using the HDL code for real-time implementation. The decision tree algorithm for the given Pill separator dataset is derived and developed using the structural model of the HDL code. The input data is fed as 5 bits and to split the 5 bits into 3 parts, the HDL code is developed using the concatenation operator in dataflow modeling. The split bits are considered for the classification of medicine based on the developed decision tree algorithm by utilizing the behavioral IF-ELSE construct in VHDL. Figure 4 depicts the simulation result of the proposed pill separator using the Decision tree algorithm in Model Sim Tool.

The synthesized HDL code is validated using the Xilinx Vivado tool to derive the schematic report as given in Figure 5. The power analysis report for the proposed method is evaluated before and after implementation of the proposed method in the Artix 7- xc7a100tcsg-1-FPGA device as shown in Figure 6. There is a slight variation in the dynamic power from 0.517W to 0.499W of the proposed method in the pre-implementation and Post-Implementation Power analysis report as Figures 6(a) and 6(b).

To develop the IC layout for the proposed method, the cadence tools namely Incisive, Genus, and Innovus are used. The developed HDL code for the proposed method is synthesized in the Genus tool to generate the schematic diagram as given in Figure 7. The schematic shows the gate-level design for the proposed pill separator and dispenser. The Innovus tool is utilized with the formation of the IC layout for the proposed method as depicted in Figure 8. The power evaluation report is generated for the IC layout of the proposed method as shown in Table 5 and Table 6. Table 5 shows the overall power report for the developed code and Table 6 presents the power report for the individual blocks used in the design. Table 7 represents the Device utilization chart for the proposed method using the Xilinx Vivado tool. The developed HDL code for the proposed method is validated for the real-time prototype using the Artix 7 FPGA device as given in Figure 9.

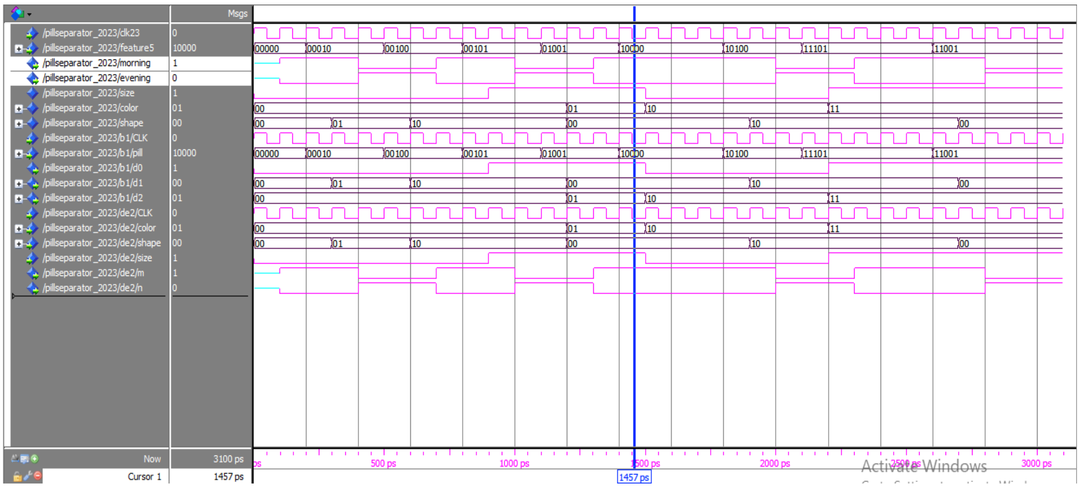


FIGURE 4: Simulation output for the Proposed Pill dispenser in Model Sim Tool

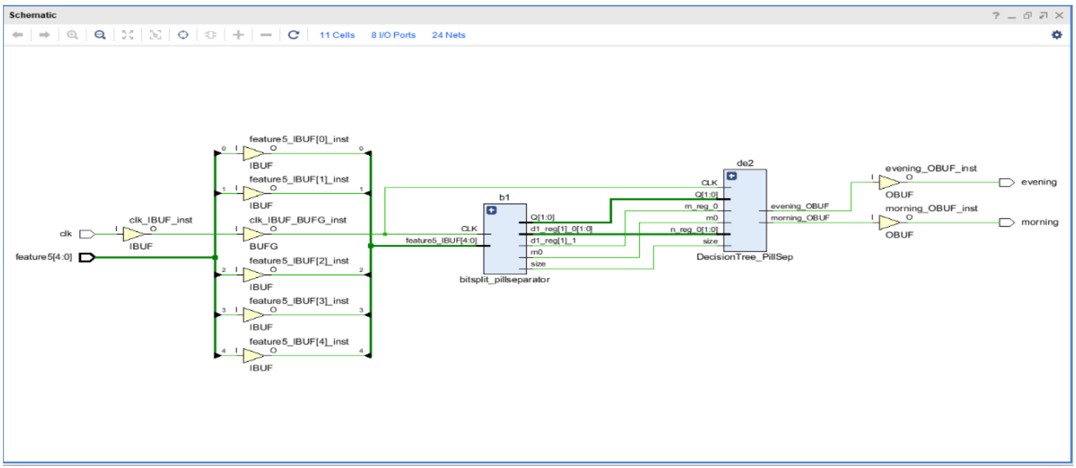
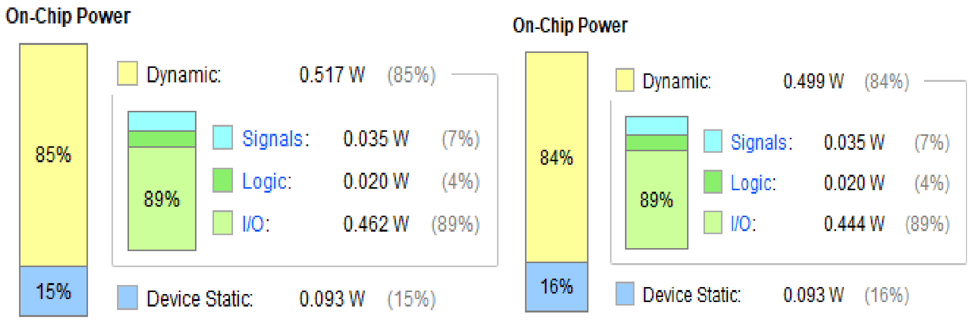


FIGURE 5: RTL schematic for the proposed Pill dispenser using the Xilinx Vivado Tool



(b)

FIGURE 6: Power Report for the proposed Pill dispenser using the Xilinx Vivado Tool

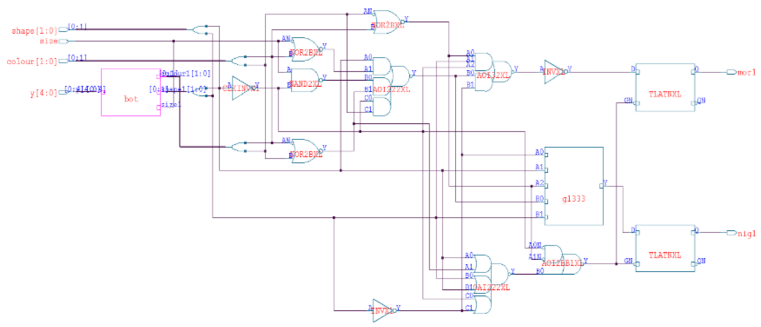


FIGURE 7: Synthesized Schematic Diagram for proposed Pill dispenser using GENUS Cadence Tool

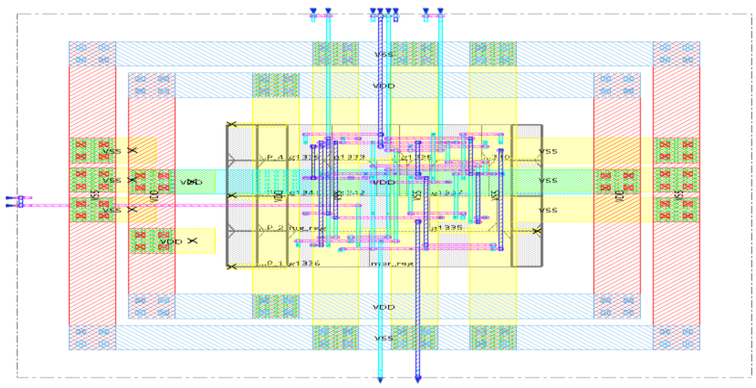


FIGURE 8: IC Layout for the proposed Pill dispenser using INNOVUS Cadence Tool

TABLE 5: Power analysis report for the proposed Pill dispenser using Cadence Tool

Total Power

Total Internal Power:	0.00154629	63.2018%
Total Switching Power:	0.00054040	22.0880%
Total Leakage Power:	0.00035990	14.7102%
Total Power:	0.00244659	

TABLE 6: Detailed Power analysis report for the proposed Pill dispenser using Cadence Tool

Group	Internal Power	Switching Power	Leakage Power	Total Power	Percentage (%)
Sequential	0.000603	2.88e-05	0.0001858	0.0008176	33.42
Macro	0	0	0	0	0
IO	0	0	0	0	0
Combinational	0.0009433	0.0005116	0.0001741	0.001629	66.58
Clock (Combinational)	0	0	0	0	0
Clock (Sequential)	0	0	0	0	0
Total	0.001546	0.0005404	0.0003599	0.002447	100

TABLE 7: Device Utilization for the proposed Pill dispenser using the Xilinx Artix 7 FPGA device

Resource	Utilization	Available	Utilization
LUT	3	63400	0.01
FF	7	126800	0.01
IO	8	210	3.81
BUFG	1	32	3.13

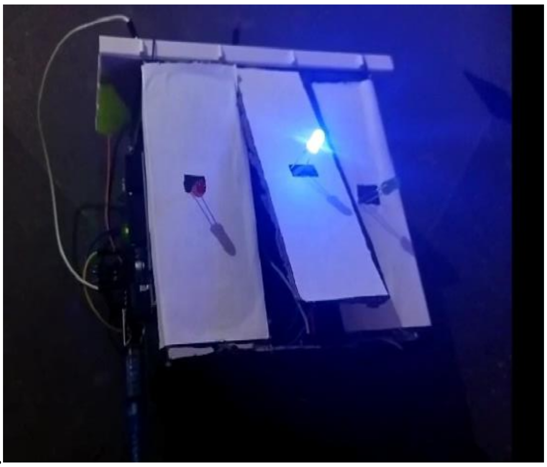


FIGURE 9: Prototype Validation in real time for the proposed Pill dispenser using FPGA device

CONCLUSION

The automated pill dispenser is successfully developed using the Decision Tree algorithm. The proposed method is synthesized and real-time validated by implementation using the Xilinx Artix-7 FPGA device. The performance analysis is evaluated for the power and area of the proposed method by utilizing the Xilinx and Cadence tool. The power and area utilized by the proposed method are low and prove to be satisfactory and feasible. The proposed method can be directed towards the automated pill dispenser robot for the Tribal people.

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