International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

VLSI Architecture for Cotton Crop Disease Detection using Machine Learning Techniques: A Study

[1]Priti Kumari, [2]Prof. Suresh S. Gawande
M. Tech. Scholar, Department of Electronics and Communication, RKDF College of Engineering, Bhabha University, Bhopal[1]
Guide, Department of Electronics and Communication, RKDF College of Engineering, Bhabha University, Bhopal[2]

Abstract:- Cotton is one of the most important commercial crops in the agricultural sector, and its production is significantly affected by various diseases that reduce crop quality and overall yield. Early and accurate identification of cotton crop diseases is essential for improving agricultural productivity and minimizing economic losses. Traditional disease detection methods mainly depend on manual observation and expert knowledge, which can be time-consuming, labor-intensive, and prone to human error. The approach integrates digital image processing, feature extraction, machine learning classification, and VLSI hardware implementation to develop an efficient automated disease detection system. Initially, cotton leaf images are collected from a suitable dataset and preprocessed using resizing, noise removal, and image enhancement techniques to improve image quality. Subsequently, relevant image features, including color, texture, and shape characteristics, are extracted to identify important disease-related patterns. Different machine learning algorithms, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR), are considered for cotton disease classification and comparative performance analysis. The best-performing classification model is selected for hardware-oriented implementation. Furthermore, the proposed machine learning architecture is mapped onto a VLSI platform by designing optimized computational units, registers, memory blocks, comparators, and control circuits. Hardware optimization techniques, including pipelining, parallel processing, and resource sharing, are considered to improve processing speed and reduce power consumption and hardware complexity. The performance of the proposed system is evaluated using classification parameters such as accuracy, precision, recall, and F1-score, along with hardware parameters including area utilization, power consumption, and propagation delay. The proposed architecture aims to provide an accurate, low-power, area-efficient, and high-speed solution for automated cotton crop disease detection, supporting the development of intelligent and real-time precision agriculture applications.

Keywords: Cotton Crop Disease Detection, VLSI Architecture, Machine Learning, Image Processing, Feature Extraction, Random Forest, Support Vector Machine, K-Nearest Neighbors, Hardware Optimization, Smart Agriculture.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

I. INTRODUCTION

Agriculture plays an important role in the economic development of many countries, particularly in developing nations such as India. It provides employment opportunities to a large population and contributes significantly to national income. Among various agricultural crops, cotton is one of the most important commercial crops because of its extensive use in the textile and garment industries. Cotton cultivation supports millions of farmers and contributes to industrial and economic development. However, cotton production is frequently affected by different plant diseases caused by fungi, bacteria, viruses, and environmental conditions. These diseases affect the growth and quality of cotton plants, resulting in reduced crop yield and financial losses for farmers. Therefore, early and accurate identification of cotton crop diseases is essential for improving agricultural productivity and supporting effective disease management [1].

Traditional methods of cotton disease detection mainly depend on manual observation and visual inspection by agricultural experts. Although these methods are commonly used, they require considerable time and experience to identify different disease symptoms accurately. Furthermore, manual inspection becomes difficult when monitoring large agricultural fields, and similar visual symptoms may lead to incorrect disease identification. With the advancement of artificial intelligence, machine learning, digital image processing, and VLSI technology, automated disease detection systems have become an effective approach for improving agricultural monitoring and classification accuracy [2, 3].

Machine Learning (ML) techniques provide efficient solutions for identifying and classifying cotton crop diseases using image-based information. Different classification algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR), can be applied to analyze extracted image features and recognize disease patterns. SVM performs classification by identifying an optimal decision boundary between different classes, whereas KNN classifies samples based on the distance between neighboring data points. Decision Tree uses a sequence of conditional decisions, while Random Forest combines multiple decision trees to improve classification reliability. Logistic Regression estimates the probability of a sample belonging to a particular disease category. The comparative analysis of these machine learning algorithms helps identify a suitable classification technique for the proposed cotton disease detection system [4].

Digital image processing plays an important role in improving the quality of cotton leaf images before classification. Initially, the collected images undergo preprocessing operations such as resizing, noise removal, normalization, and image enhancement. These operations reduce unwanted variations and improve the quality of the input images. Subsequently, feature extraction techniques are employed to identify important characteristics, including color information, texture patterns, and shape descriptors. The extracted features are supplied to different machine learning algorithms for training, testing, and disease classification. The

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

performance of these algorithms can be compared using evaluation metrics such as accuracy, precision, recall, and F1-score [5, 6].

Although machine learning algorithms provide effective disease classification, their implementation on conventional computing platforms may require considerable computational resources, memory, and processing time. These limitations become important when developing real-time agricultural monitoring devices with restricted hardware resources. Very Large-Scale Integration (VLSI) technology provides an effective solution for designing compact, high-speed, and low-power hardware architectures. VLSI implementation enables the integration of multiple computational units, memory elements, registers, comparators, and control circuits on a single chip. Furthermore, architectural optimization techniques such as pipelining, parallel processing, and resource sharing can improve computational efficiency and reduce hardware complexity.

In this research, a VLSI architecture is proposed for cotton crop disease detection using different machine learning techniques. Initially, cotton leaf images are collected from a suitable dataset and preprocessed to improve image quality. Relevant features are extracted from the processed images and supplied to different machine learning classifiers, including SVM, KNN, DT, RF, and LR. A comparative performance analysis is conducted to identify the most suitable classification algorithm. Subsequently, the selected machine learning model is considered for VLSI hardware implementation. The proposed hardware architecture consists of input processing units, feature extraction modules, memory elements, computational circuits, classification units, and control logic. The architecture is optimized by considering hardware parameters such as area utilization, power consumption, and propagation delay [7, 8].

II. IMAGE PROCESSING

In Image processing section, initially the image is captured from the camera and further the image is processed using k means clustering for segmenting the image. The processed image is then edge detected using three different edge detection techniques. The edge detection techniques used are sobel, prewitt and canny algorithm. The diseased sample banana leaf has been taken for the edge detection analysis. Amongst the three edges detection methods used, canny edge detection algorithm gives the better and reliable detection. Owing to its optimality to meet with the three criteria for edge detection and the simplicity of process for implementation, it became one of the most popular algorithms for edge detection method [9].

As discussed earlier, IoT and Image processing are combined together in agricultural field in order to increase product yield and to reduce the crop failure. We focused on plant failure due to environmental factors through IoT technology. IoT system includes sensors, Arduino and a camera that regularly captures the plant. The color, texture, shape and area of the leaf are the parameters also considered in this work. After examine the conditions of the plants we go for image processing. In addition to the environmental factors, the plant with a diseased leaf can also be identified using Image processing. Based on the output and constraints the pesticides will be sprayed for the crop/plant where the disease is identified. If there is any change that corresponds

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

to the deterioration in the plants growth, the farmer is immediately informed. Early diagnosis will thus help in taking the necessary actions to increase the produce and reduce failure of crops [10].

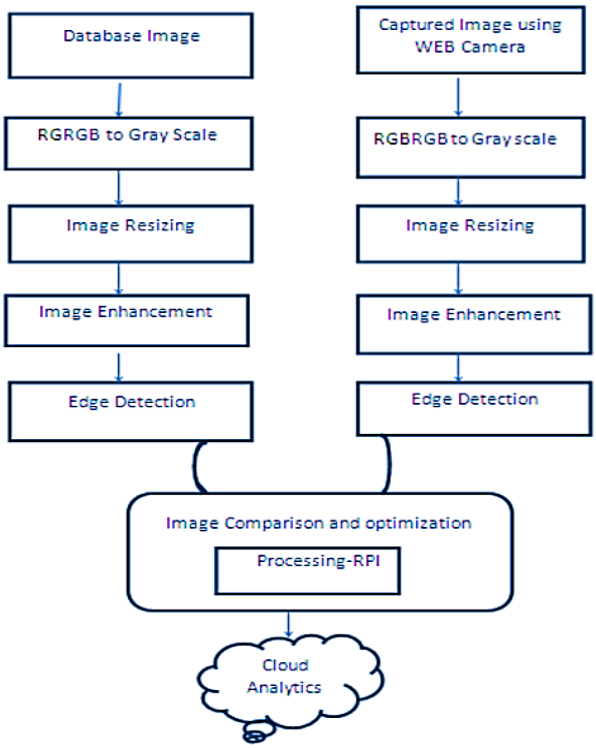

Figure 1: Block diagram of Image Processing

III. LITERATURE REVIEW

R. Kumar et al. [1], the presence of cotton plant wells is extremely important for maintaining agricultural productivity, and early detection of diseases plays a critical role in achieving this goal. This study presents a comprehensive approach to creating machine learning systems that can identify diseases in cotton systems by analyzing leaf images. The survey includes stages such as obtaining data records, preprocessing data, training models, developing ensemble models, assessing models, and analyzing results. Several machine learning models are trained and evaluated to determine whether cotton leaves can be classified as "healthy or "disease." These models include Random Forest, Support Vector Machines (SVMs), Multi-Class SVMs, and Ensemble models. This test provides a practical and visually beneficial system for recognizing diseases that may contribute to disease prevention, thus improving both yield and quality. This work highlights the importance of continuous improvement by periodically updating the model and examining the possibilities of advanced technologies such as deep learning.

I. Ahmed et al. [2], agricultural harvest production is possible through photographs of plant leaves and automated identification of agricultural harvest diseases and unhealthy regions, and

advances in technology that increases production. Machine learning is used to identify agricultural harvest diseases and image processing techniques such as image intake, preprocessing, segmentation, characterization extraction, support vector machines (SVMs), folding networks (CNNs), K-nearest neightre, and Gray-level co-ocular matrix (GLCMs). This method uses photographs to recognize plant diseases. GLCM extracts structural properties from photographs. k-mean clustering segment input image. The SVM classifier improves the performance of existing algorithms by splitting the input image. The approach is to eliminate human participation and improve farmer procurement. Farmers rarely produce high harvests or reduce their income. Nutrient deficiency, soil moisture, temperature fluctuations, etc. Because of this, this analytical approach can use different techniques to improve the accuracy of the victim. During this evaluation, we will develop predictive tools for plant diseases and propose new ways to become uncomfortable. The system provides information about certified users.

S. Bondre et al. [3], awareness of agricultural diseases plays an important role in the world of intellectual agriculture. For agricultural production to increase sustainably, identifying plant diseases must be efficient. Plant abnormalities affected by viruses, insects, malnutrition and lack of bad weather have traditionally been diagnosed by human experts. Two highly developed technologies for machine learning synonymous with deep learning (DL) and transfer learning, further developments of artificial intelligence technology in recent years, have been used to identify agricultural diseases. However, there are various obstacles to the widespread use of these approaches. This paper specifically examines DL and transfer learning and discusses recent developments using these advanced technologies to recognize agricultural disease photos. Many DL architectures have recently been adopted along with visualization tools. This is extremely important for identifying labels and classifying plant diseases. The analysis and evaluation of these two approaches indicate that transfer learning is a better choice when data is available for agricultural diseases. Next, this paper examines the most important issues that must be addressed for research in this field in order to advance. B. Optimizing image data records creation, collection of big data auxiliary domains, and transfer learning. Building a technically feasible image identification system for agricultural diseases involves the creation of image data sets collected under actual cultivation conditions. The purpose of this study is to learn more about DL skills in plant disease detection to increase the efficiency and accuracy of devices in future research.

M. M. Islam et al. [4], cotton is known in the agricultural industry as "white gold." Agriculture is the main source of Bangladesh's economic revenue, and the country's economy is heavily dependent on agriculture. Our country's soil and water resources are fertile and the climate is mild. However, many diseases affect plant production, causing major harvest losses, which put the lives of helpless farmers at risk. Previous reports have shown that approximately 70-80% of cotton diseases are leaf disease and 30-20% pest disease. Experts usually use the naked eye to identify and identify plant diseases and pests that can result from poor identification accuracy. As a result, early detection of cotton disease using an AI-based system can help increase cotton production by significantly demonstrating leaf disease. In this study, we proposed a DL-based cotton leaf disease approach with detection of fine-tuning transfer learning (TL) by setting layers and parameters of existing TL algorithms. We also examined the performance of several fine-tuning models such as VGG-16, VGG-19, Inception-V3, and Xception of cotton data records that

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

have been published to predict cotton disease. The study showed that the Xception model yielded the highest accuracy of 98.70% and was chosen to increase cotton production to develop web-based intelligent applications for the prediction of cotton disease in agriculture. Therefore, our model can diagnose the accurate diagnosis of cotton disease and provide a new window for automatic leaf disease diagnosis of other plants.

R. Mahum et al. [5], potato disease management plays a valuable role in the agricultural sector. This is because it can lead to significant losses in plant production. Therefore, timely detection and classification of potato disease is required to minimize losses. However, it is time to take on the task and demand human effort. Therefore, accurate automated technology is required for timely detection and classification to address the above challenges. There are methods based on machine learning and deep learning methods that use existing data records. Run the H. Village data record and run only two classes with potato leaves. A highly efficient Dennenet model was used along with the additional transition layer of Dersenet-2010 to efficiently classify potato leaf diseases. Furthermore, because the training data is very unbalanced, the proposed algorithm becomes lobster when using the newly weighted cross-entry loss function. The tight connection with the power of regularization contributes to minimizing overwork during nighttime during training with small training rates of potato leaves. The proposed algorithm is a new first technique for addressing and reporting successful implementation of recognition and classification of four diseases in potato leaves. The performance of the algorithm was evaluated on a test set, resulting in an accuracy of 97.2%. Various experiments were conducted to confirm that our proposed algorithm is more consistent and capable of recognizing potato blade disease and classifying it as an existing model.

L. Goel et al. [6], agriculture is one of the most important sectors and meets the basic food needs of humanity. Plant diseases raise concerns about economic and nutritional security of federal states and hinder agricultural planning. Traditional methods to recognize plant diseases require a lot of work and time. As a result, many researchers and institutions strive to tackle these issues with the help of sophisticated technical methods. Deep learning-based detection of plant diseases offers considerable advancement and hope compared to classical methods. When these techniques are trained on large, high-quality datasets, these techniques recognize robust diseases of plant leaves at the early stages. This study was examined in three different areas: disease classification, detection and segmentation of system leaf disease, and thoroughly checked data records that were published simultaneously. This systematic overview provides a comprehensive assessment of the current literature and describes the most popular deep learning architectures, the most frequently investigated systems, data records, challenges, and various perspectives. Provides researchers working in the agricultural sector. Furthermore, the biggest challenges in the field of disease detection in agriculture are involved. Therefore, this study provides valuable information and appropriate solutions based on deep learning applications for agricultural sustainability.

IV. VLSI ARCHITECTURE

VLSI (Very Large-Scale Integration) architecture plays an important role in developing high-speed, low-power, and area-efficient hardware systems for real-time image processing and classification applications. In the proposed research, a machine learning-based VLSI architecture

is designed for automated cotton crop disease detection. The architecture integrates digital image processing, feature extraction, machine learning classification, and hardware optimization techniques to identify different cotton leaf diseases efficiently. The main objective is to convert the computational operations of the selected machine learning algorithm into optimized hardware structures that can be implemented using FPGA or ASIC technology [10, 11].

The proposed architecture initially receives cotton leaf images through an input interface, where the image data is stored in memory for further processing. The preprocessing unit performs image resizing, noise removal, normalization, and enhancement to improve image quality. After preprocessing, the feature extraction unit calculates important characteristics such as color, texture, and shape information from the cotton leaf images. These extracted features are transferred to the machine learning classification unit, where different algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR), are considered for disease classification. A comparative analysis is performed to identify the most suitable classification model based on accuracy, precision, recall, and F1-score [12, 13].

V. CONCLUSION

The approach integrates digital image processing, feature extraction, machine learning classification, and hardware implementation to improve disease detection performance. Initially, cotton leaf images are collected and preprocessed using resizing, noise removal, normalization, and image enhancement techniques. Subsequently, important image features, including color, texture, and shape characteristics, are extracted and supplied to different machine learning algorithms, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR). A comparative analysis of these classifiers is performed using accuracy, precision, recall, and F1-score to identify the most suitable classification model.

Furthermore, the selected machine learning classifier is mapped into a VLSI architecture consisting of computational units, multipliers, adders, comparators, registers, memory blocks, multiplexers, and control circuits. Different hardware optimization techniques, including pipelining, parallel processing, fixed-point arithmetic, resource sharing, and clock gating, are considered to improve computational efficiency and reduce hardware complexity. The proposed architecture is evaluated using important hardware parameters such as Look-Up Tables (LUTs), Flip-Flops, power consumption, area utilization, propagation delay, and operating frequency. The integration of machine learning techniques with optimized VLSI hardware aims to provide accurate disease classification with reduced processing time, lower power consumption, and efficient hardware utilization. Overall, this research can contribute to the development of

intelligent, high-speed, and low-power agricultural monitoring systems for real-time cotton crop disease detection and improved agricultural productivity.

REFERENCES

[1] R. Kumar *et al*., "Hybrid Approach of Cotton Disease Detection for Enhanced Crop Health and Yield," in *IEEE Access*, vol. 12, pp. 132495-132507, 2024
[2] I. Ahmed, G. Habib and P. K. Yadav, "An approach to identify and classify agricultural crop diseases using machine learning and deep learning techniques", *Proc. Int. Conf. Emerg. Smart Comput. Informat. (ESCI)*, pp. 1-6, Mar. 2023.
[3] S. Bondre and D. Patil, "Recent advances in agricultural disease image recognition technologies: A review", *Concurrency Computation Pract. Exper.*, vol. 35, no. 9, Apr. 2023.
[4] M. M. Islam, M. A. Talukder, M. R. A. Sarker, M. A. Uddin, A. Akhter, S. Sharmin, et al., "A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture", *Intell. Syst. Appl.*, vol. 20, Nov. 2023.
[5] R. Mahum, H. Munir, Z.-U.-N. Mughal, M. Awais, F. S. Khan, M. Saqlain, et al., "A novel framework for potato leaf disease detection using an efficient deep learning model", *Hum. Ecol. Risk Assessment Int. J.*, vol. 29, no. 2, pp. 303-326, Feb. 2023.
[6] L. Goel and J. Nagpal, "A systematic review of recent machine learning techniques for plant disease identification and classification", *IETE Tech. Rev.*, vol. 40, no. 3, pp. 423-439, May 2023.
[7] C. Sarkar, D. Gupta, U. Gupta and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges", *Appl. Soft Comput.*, vol. 145, Sep. 2023.
[8] J. Karthika, M. Santhose and T. Sharan, "Disease detection in cotton leaf spot using image processing", *J. Phys. Conf. Ser.*, vol. 1916, no. 1, 2021.
[9] Y. Yuan, L. Chen, H.Wu, and L. Li, ‘‘Advanced agricultural disease image recognition technologies: A review,’’ Inf. Process. Agricult., vol. 9, no. 1, pp. 48–59, Mar. 2022.
[10] V. Kathole and M. Munot, ‘‘Deep learning models for tomato plant disease detection,’’ in Advanced Machine Intelligence and Signal Processing. Singapore: Springer, 2022, pp. 679–686.
[11] Q. Pan, J.-F. Qiao, R. Wang, H.-L. Yu, C. Wang, K. Taylor, and H.-Y. Pan, ‘‘Intelligent diagnosis of northern corn leaf blight with deep learning model,’’ J. Integrative Agricult., vol. 21, no. 4, pp. 1094–1105,Apr. 2022. V. Petsiuk. (2019).
[12] U. Chauhan, ‘‘ResTS: Residual deep interpretable architecture for plant disease detection,’’ Inf. Process. Agricult., vol. 9, no. 2, pp. 212–223, Jun. 2022. M. Turkoglu, B. Yanikoğlu, and D. Hanbay, ‘‘Plantdiseasenet: Convolutional neural network ensemble for plant disease and pest detection,’’ Signal, Image Video Process., vol. 16, no. 2, pp. 301–309, 2022.
[13] Vallabhajosyula, V. Sistla, and V. K. K. Kolli, ‘‘Transfer learning-based deep ensemble neural network for plant leaf disease detection,’’ J. Plant Diseases Protection, vol. 129, no. 3, pp. 545–558, Jun. 2022.
[14] Chen, Z. Yuan, S. Chen, and X. Zou, ‘‘Plant disease recognition model based on improved YOLOv5,’’ Agronomy, vol. 12, no. 2, p. 365, Jan. 2022. A. M. Roy, R. Bose, and J. Bhaduri, ‘‘A fast accurate fine-grain object detection model based on YOLOv4 deep neural network,’’ Neural Comput. Appl., vol. 34, no. 5, pp. 3895–3921, Mar. 2022.
[15] Wang, X. He, K. Feng, and H. Zhu, ‘‘Plant disease detection and classification method based on the optimized lightweight YOLOv5 model,’’ Agriculture, vol. 12, no. 7, p. 931, Jun. 2022.