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Custom hardware design for peripheral artery disease detection: Field-programmable gate arrays and application-specific integrated circuits

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Abstract

Atherosclerotic disorders, such as peripheral artery disease (PAD), have a significant negative impact on patient outcomes. Inadequate treatment and poor detection rates can result in cardiovascular complications and limb loss. There is great promise for improving the detection and treatment of PAD and other medical disorders through machine learning (ML) and artificial intelligence (AI) techniques. This paper highlights the use of field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) to implement the fundamental ideas of AI and ML, specifically in the treatment of PAD. It emphasizes how these technologies can enhance drug selection, improve patient care, and refine disease phenotyping. This paper also describes how the integration of AI and ML with FPGA and ASIC technology can provide accurate and effective solutions to complex medical challenges, representing a significant breakthrough in medical analytics.

Keywords: Application-Specific Integrated Circuits, Field-Programmable Gate Arrays, Machine Learning, Peripheral Arterial Disease

1. Introduction

The cardiovascular condition known as peripheral artery disease (PAD) is caused by atherosclerosis, which restricts blood flow to the arteries and surrounding tissues (Campia et al., 2019; Criqui et al., 2015; Nordanstig et al., 2020; Rafnsson et al., 2020). After coronary artery disease and stroke, PAD is now the third most common atherosclerotic cardiovascular disease in terms of patient population (Criqui et al. 2015; Olin, 2000; Venkatesh et al., 2017). The most common symptom of PAD is intermittent claudication, an ischemic pain that arises when working leg muscles do not receive enough oxygen (Schorr et al., 2013). Over time, sedentary behavior tends to increase in PAD patients. Fig. 1. shows the difference between a normal artery and an artery with plaque.

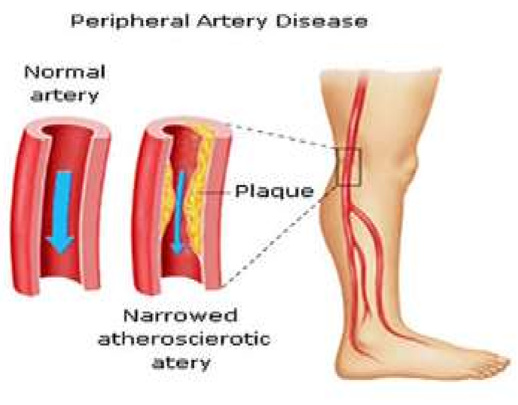

Fig. 1. Normal artery and artery with plaque. (Reproduced from Dr. Abhilash, 15 December 2016)

Furthermore, functional impairment usually occurs before the diagnosis of PAD, and silent, undiagnosed PAD is linked to worse outcomes compared to intermittent claudication (Thrall et al., 2018). It was estimated that more than 237 million adults aged 25 and older had PAD over the past decade, with prevalence sharply rising with age (Lareyre et al., 2023). Epidemiologic research also indicates a marked rise in the prevalence of PAD, particularly in low- and middle-income nations, suggesting the potential for a widespread PAD pandemic (Criqui & Aboyans, 2015). Treatments that are frequently employed include medication, surgery, and lifestyle changes; however, these may cause serious side effects and may not be suitable for everyone (Venkatesh et al., 2017). PAD risk is strongly associated with traditional cardiovascular risk factors, such as diabetes, smoking, and advanced age (Criqui & Aboyans 2015) Historically, PAD has received less attention than coronary artery disease and stroke, but in recent years, more focus has been paid to it, leading to new epidemiological advances (Olin 2000). A more severe form of cardiovascular disease that requires additional clinical care, is known as polyvascular disease. This disease is characterized by atherosclerosis in several artery beds. PAD can raise the risk of unfavorable outcomes by an equal amount or greater than that of heart disease or stroke (Schorr et al., 2013). The classification of PAD is shown in Fig. 2.

Early detection of PAD would allow for timely treatment that can slow the disease's progression, hence lowering the risk of major cardiovascular events. Nevertheless, in a primary care context, 40–60% of patients with PAD remain undiagnosed (Thrall et al., 2018). Ankle-brachial index (ABI) testing is the standard diagnostic procedure, but it is an expensive, highly specialized test that needs trained technologists in a vascular lab setting (Currie, 2019). Although physiological factors can impact the pulse wave recording technique, pulse wave measurements have shown potential for effectively detecting PAD, similar to ABI testing (Altman et al., 2024). Peripheral blood flow is necessary for a pulse wave to occur, and sympathetic nerve input, rather than vascular patency may influence pulse wave characteristics (Altman et al., 2024). Furthermore, by lowering blood flow, severe congestive heart failure can mimic inflow illness (Altman et al., 2024). Further investigation is required to establish the screening and diagnostic validity of pulse wave velocity measurements, which are a reliable hemodynamic measure for detecting PAD (Iglehart, 2006). Because PAD can mimic other conditions and is associated with aging, its diagnosis can be challenging. To help healthcare providers identify high-risk patients in their everyday clinical

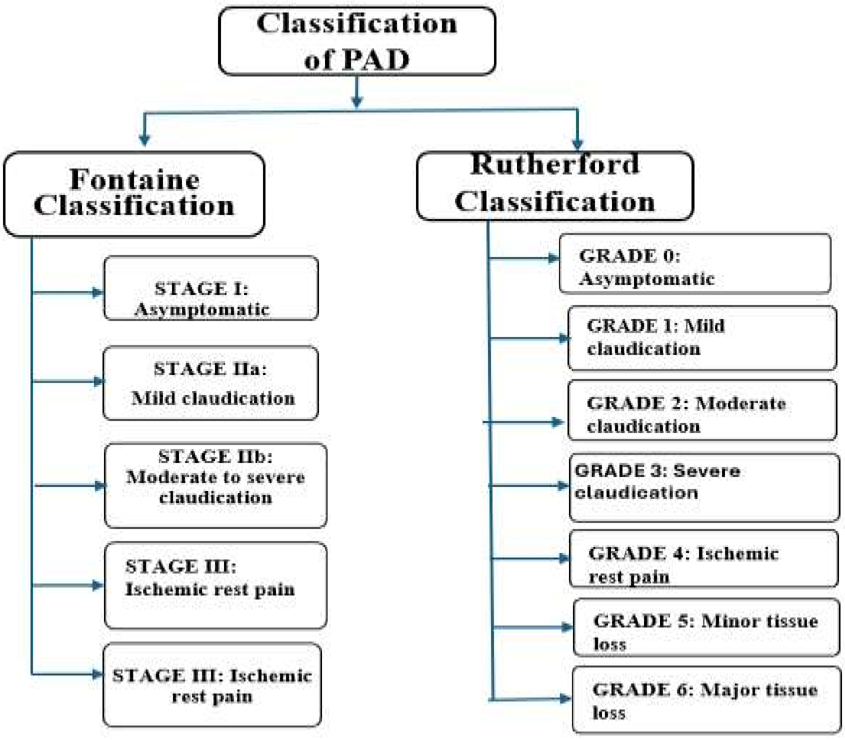

Fig. 2. Classification of peripheral arterial diseases (PAD).

practice, a non-invasive screening method is needed. The symptoms of PAD include claudication, unusual leg discomfort, and critical limb ischemia, which can result in ulcerations and possibly amputation. PAD is defined by an ABI of less than or equal to 0.90 (Nordanstig et al., 2020).

1.1. Prevalence and Clinical Significance of Peripheral Artery Disease

Prevalence: PAD involves the atherosclerotic narrowing or occlusion of arteries other than the coronary arteries and the aorta. It affects various arteries, including the carotid, vertebral, mesenteric, renal, and limb arteries.

Risk Factors: Common risk factors include smoking, hypertension, dyslipidemia, diabetes, and autoimmune/inflammatory conditions.

Clinical significance: PAD is associated with increased cardiovascular morbidity and mortality, and it significantly impairs quality of life.

Screening and diagnosis: Screening for PAD involves assessing risk factors and symptoms, as well as using tools like the ABI and various imaging modalities.

1.2. Challenges in Current Diagnostic Methods

Although PAD, often caused by atherosclerosis, can affect any artery outside the heart and brain, it is frequently linked to conditions of the lower limbs. The prevalence of PAD is increasing worldwide, especially in low- and middle-income nations, with significant rises in cases (Aboyans et al., 2017). Among the risk factors include diabetes, hypertension, and smoking (Criqui & Aboyans 2015). Chronic limb-threatening ischemia and intermittent claudication are two possible indications of PAD (Aboyans et al., 2018). Management of PADs typically involve secondary prevention, risk factor elimination, and early diagnosis (Venkatesh et al., 2017). In severe cases, revascularization may be necessary in addition to medications and lifestyle modifications (Adegbola et al., 2022).

1.3. Invasive and Non-Invasive Methods for Peripheral Artery Disease Diagnosis

Since the 1670s, various invasive and non-invasive diagnostic tools have been developed to address peripheral vascular diseases. These tools help in precise diagnosis and treatment planning. Imaging methods for PAD are categorized into non-invasive and invasive modalities, each with distinct advantages, disadvantages, and associated costs (Lareyre et al., 2023).

1.3.1. Non-Invasive Methods

1. Color duplex ultrasound

Benefits: Non-invasive, non-ionizing, requires no contrast agent, provides hemodynamic data, and is useful for follow-up.

Cons: Requires an operator, it has a narrow range of vision; takes longer to examine; and can't evaluate calcified vessels as thoroughly.

2. Computed tomography (CT) angiography

Benefits: Non-invasive, low cost, high availability, quick three-dimensional (3D) imaging, excellent spatial resolution, and the ability to post-process data.

Cons: Limited evaluation of calcified and infra-popliteal vessels; iodinated contrast material is necessary; ionizing radiation is used.

3. CT with dual energy

Benefits: High spatial resolution, exceptional image quality in remote areas, and the ability to examine tissue in greater detail.

Cons: Limited accessibility and requires specialist equipment; ionizing radiation is used.

4. CT using photon counting

Benefits: Minimizes blooming artifacts, provides intrinsic spectral information, results in minimal radiation exposure, offers excellent contrast-to-noise ratio, and has high spatial resolution.

Cons: Restricted accessibility and involves ionizing radiation.

5. Magnetic resonance imaging (MRI)

Benefits: Non-invasive, does not require contrast material, offers high resolution, provides flow-independent assessment of vessels below the knee, delivers excellent soft tissue contrast for evaluating plaque, provide hemodynamic information, and uses gadolinium-based contrast that is more tolerable for patients with impaired renal function.

Cons: Greater cost compared to CT; longer acquisition time; limited assessment of calcifications due to certain procedures; claustrophobic difficulties; limitations with non-MRI conditional devices.

1.3.2. Invasive Methods

1. Digital subtraction angiography

Advantages: High resolution, fast.

Disadvantages: Invasive, requires iodinated contrast material, limited ability to assess vessel wall.

2. Intravascular ultrasound

Advantages: Provides widespread, detailed diagnostic information on lumen size, vessel wall, and plaque burden.

Disadvantages: Susceptible to artifacts, lower frame rate, operator dependent.

3. Optical coherence tomography

Advantages: High resolution, provides both two-dimensional and 3D images, suitable for smaller vessels.

Disadvantages: Limited penetrative depth, restricted field of view, requires saline irrigation accompanied by inflow occlusion.

4. Angioscopy

Advantages: Direct visualization of vessel wall and wall-associated structures, provides colored images.

Disadvantages: Cannot measure disease presence, plaque volume, content, or depth; requires saline irrigation accompanied by occlusion.

This comprehensive comparison aids in selecting the most appropriate imaging modality based on clinical needs, patient condition, and available resources (Lareyre et al., 2023).

1.4. Advantages over Traditional Methods

the Management of PAD involves revascularization, advanced diagnostics, and post-care to prevent complications. Challenges include embolization, calcification, and restenosis. New treatments feature less invasive methods, drug-eluting technologies, and biomimetic stents, enhancing outcomes. Machine learning (ML) and real-time data improve early diagnosis and treatment of PAD (Beckman et al., 2021). Nanotechnology in testing offers cost-effective, faster, more accurate, and sensitive solutions, aiding in the identification and management of PAD (Geiss et al., 2019). With these technological advances, PAD can now be diagnosed and treated with greater accuracy, potentially improving patient outcomes and quality of life (Elbadawi et al., 2021).

Building on the progress in PAD treatment, Section 2 provides an overview of ML, including its various types. In Section 3, we explore how ML is applied in the medical field, particularly for diagnosing PAD. Section 4 focuses on the use of ML with field-programmable gate arrays (FPGA) technology for PAD diagnosis, discussing both its advancements and limitations. Section 5 examines how ML integrates with artificial intelligence (AI) and application-specific integrated circuits (ASIC) technologies in medical diagnosis, highlighting improvements with AI performance and efficiency for PAD diagnosis. The review will conclude with proposed work and final thoughts.

2. Artificial Intelligence Technologies in Healthcare

Artificial intelligence and ML can greatly enhance healthcare by predicting illness outcomes, patient readmissions, and therapy responses (Jiang et al., 2017). Deep learning improves diagnostic accuracy in medical image analysis using MRIs, CT scans, and X-rays (Litjens et al., 2017). Natural language processing extracts valuable information from clinical documentation, improving decision-making and data accuracy. AI in genomic medicine identifies genetic markers, understands genetic variations, and develops personalized therapies, thus advancing precision medicine. ML accelerates drug discovery, reducing risk and improving decision-making in target validation and drug design. In personalized medicine, AI tailors treatments based on genetic profiles and previous responses, optimizing success rates and minimizing adverse effects (Kourou et al., 2015).

Artificial intelligence in robotic surgery enhances precision, reduces errors, and improves patient outcomes (Hashimoto et al., 2018). Wearable sensors enable remote patient monitoring, with AI analyzing data and alerting healthcare providers to health trends (Rojas & Wang, 2020). AI also improves electronic health record (EHR) management, enhancing data accuracy, care coordination, and administrative efficiency. Addressing concerns about patient privacy, bias, and transparency is crucial for the ethical use of AI in healthcare (Rojas & Wang, 2020).

2.1. Machine Learning and Its Applications in Medical Diagnosis of Peripheral Artery Disease

The ability of machine to independently simulate intelligent activity using ML has significantly advanced in the field of computer science (Bini, 2018), leading to its increasing application in various fields, including medicine. The use of AI in medicine has expanded rapidly, with collaborations between the medical field and AI garnering significant attention from the global economy, particularly in 2016 (Buch et al., 2018). AI's role in medicine primarily involves automating diagnostic procedures and managing patient care, which allows medical professionals to focus on more complex, non-automatable tasks.

In medical applications, ML is typically categorized as supervised learning, where output variables are predicted from input data, and unsupervised learning, which involves clustering different groups based on specific interventions. This growing utilization of ML is not limited to direct medical care but extends to areas like human resources, allowing practitioners and specialists to build sophisticated models and extract valuable medical knowledge.

Machine learning predictive models are particularly useful in clinical settings, where they can improve decision-making and even autonomously diagnose various disorders (Criqui et al., 2015; Schorr et al., 2013). Furthermore, corporations leveraging ML in drug prescription can help physicians identify new medical opportunities, potentially saving lives by accurately detecting pathologies (Lo et al., 2018). Additionally, by reducing medical expenses, stabilizing patient flow, and improving data quality, ML models offer a more effective alternative to traditional diagnostic methods (Napolitano et al., 2016).

The next section explores how ML is applied to PAD, how it enhances diagnostic accuracy, facilitates early detection, and ultimately improves patient outcomes. By analyzing large sets of vascular data, ML models are instrumental in identifying patterns that may go unnoticed using traditional diagnostic methods. This section delves into the effectiveness of these techniques, providing actionable insights that support clinicians in making more informed decisions regarding PAD treatment and management.

It also highlights how ML could enhance clinical care and medical research, especially when applied to electronic health data (Jordan & Mitchell, 2015). Moreover, ML methods are emphasized for their capacity to identify illnesses and forecast health outcomes. For example, predicting the course of diabetes from electronic health information and classifying skin cancer from photos are two notable applications (Esteva et al. 2017).

Researchers have gained new insights from clinical incident reports by integrating ML with natural language processing strategies (Ong et al., 2012) integrated in social networking sites. Evaluations of physician performance and patient testimonials following beneficial cancer therapies have been enhanced using ML (Ong et al., 2012).

Current PAD treatments often use a generic approach, but research is exploring more options beyond aspirin, statins, and smoking cessation, despite their higher costs and risks (Flores et al., 2021). ML models can optimize PAD treatment for patients with comorbidities by analyzing drug interactions and polypharmacy side effects. Training these algorithms on PAD patients' data can help create synchronized treatment plans, replacing reductionist approaches with AI that identifies PAD subgroups and integrates polypharmacy and pharmacogenetics data. Advanced data science can also assess long-term therapy safety in real-world contexts, addressing clinical trial exclusions, like those with congestive heart failure on cilostazol, which showed no adverse effects (Brass et al., 2006).

Machine learning can identify complex PAD risk factors using EHR data but requires structured data and portable analysis pipelines. Improved prediction models, such as those for surgical site infections and limb ischemia post-revascularization, can enhance PAD treatment and outcomes (Brass et al., 2006). Combining clinical and imaging data, like Doppler waveforms and CT angiograms, using ML and computer vision can further improve PAD diagnosis and reduce invasive procedures (Misra et al. 2019). Different researchers have applied various ML algorithms to a range of diseases and have assessed their respective advantages and disadvantages. For diseases similar to PAD, these findings have been summarized in Table 1, highlighting the advantages and disadvantages of each algorithm.

Fig. 3 depicts the number of papers published on ML for PAD from 2002 to 2024, with a substantial upward trend. The data, derived from the Scopus database, reveal consistent growth in publications over time, with a notable surge in recent years as the use of ML in healthcare has gained traction.

2.2. Types of Machine Learning Techniques Used

Machine learning techniques are becoming increasingly effective in risk assessment, disease prognosis, and image-based diagnosis. With a wide range of applications, ML is one of the fastest-growing fields in computer science. It involves the automatic identification of significant patterns in data. Giving algorithms the capacity to learn and adapt is the focus of ML tools (Shalev-Shwartz & Ben-David 2014). ML algorithms are classified based on their intended outcomes. Supervised learning converts inputs into desired outputs and is common due to its role in

Table 1. Types of machine learning algorithms and their advantages and disadvantages.

ML algorithm	Advantages	Disadvantages
KNN	- A model that is inexpensive and simple to use. - Is utilized in both regression and classification. - Handles multiclass situations seamlessly.	- The computation is quite high. - Classification costs for unknown records are comparatively high. - Elevated sensitivity to irrelevant features.
K-Means	- Simple to execute. - More effective when variables are larger than hierarchical clustering.	- It is challenging to estimate the K value. - Performance declines with a globular cluster. - Sensitive to noise and anomalies.
SVM	- Can handle linear and nonlinear data. - Lower likelihood of overfitting. - Scales well with high-dimensional data.	- Performance degrades when dealing with huge datasets. - Choosing a good kernel function is challenging. - Less effective in noisy datasets.
Naïve Bayes	- Convenient for large datasets. - Handles both discrete and continuous data. - Can be applied to both multiple and binary classification. - Insensitive to irrelevant features.	- Computationally demanding, particularly for models with many variables. - Models that have been properly trained and applied may occasionally underperform. - Lack complexity.
Logistic regression	- Computationally effective. - Simple regularization. - No scaling is needed for input features.	- Solving a nonlinear problem is challenging. - Risk of overfitting.
Decision tree	- Utilized for classification as well as regression. - Simple management of both categorical and numerical data.	- Overfitting could happen if the tree is constructed repeatedly. - Larger trees become challenging to understand.
Random Forest	- Applicable to both classification and regression problems. - Solves overfitting issues in a decision tree.	- Training takes a long time. - Complexity increases.
Deep learning	- Automatically identifies features. - Applicable to several types of data.	- For training, GPUs are required. - Complicated data models make training extremely expensive.

Abbreviations: GPU: Graphics Processing Units; KNN: K-Nearest Neighbors; SVM: Support Vector Machine.

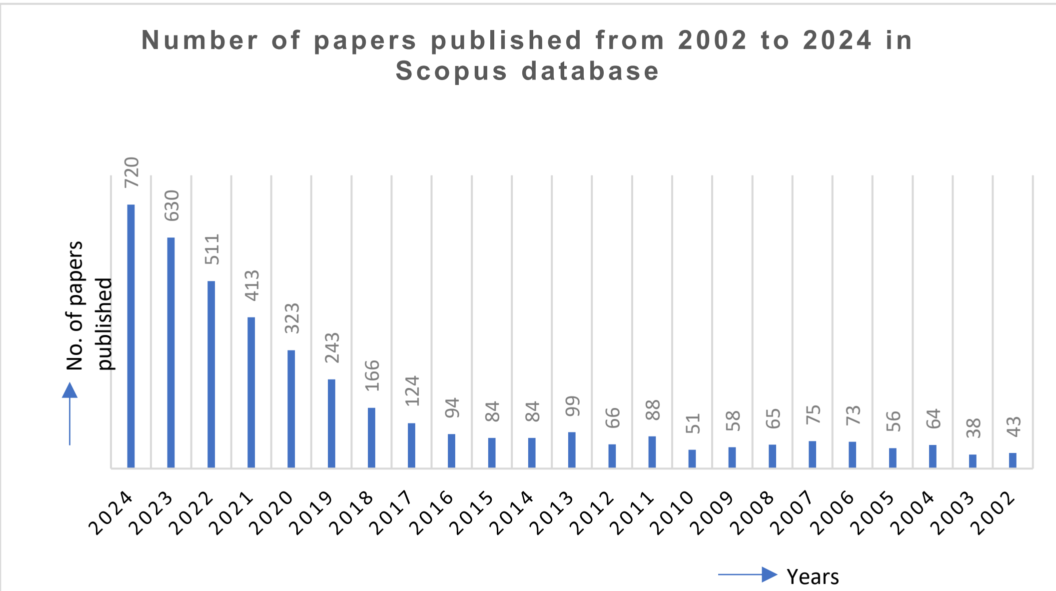

Fig. 3. Number of papers published on machine learning for peripheral arterial disease from 2002 to 2024. Source: http://www.webofscience.com

teaching classification systems. The complexity of data generation has led to the adoption of both supervised and unsupervised techniques (Shalev-Shwartz & Ben-David, 2014), enabling accurate predictions on unseen data (Sarker, 2021).

2.2.1. Unsupervised Learning and Semi-Supervised Learning

Unsupervised learning allows machines to recognize patterns in unlabeled data, making it useful for tasks like clustering. Semi-supervised learning combines labelled and unlabeled data. In this approach, a supervised algorithm is trained on labeled data, while an unsupervised algorithm is used to label new instances for further training (Smiti, 2020).

2.2.2. Reinforcement Learning

By using prior experience, this ML technique enables robots or agents to determine the most optimal behavior in a given scenario. Machines gather information during training to enhance their functionality (Smiti, 2020).

Each ML algorithm has a unique set of benefits and limitations. While some are more focused on specificity or computing efficiency, others are especially excellent in terms of accuracy and sensitivity. The trade-offs highlighted in these comparisons underscore how different algorithms perform better for different datasets or tasks. Therefore, the ideal approach to use relies on the unique requirements and limitations of the application. To analyse the efficacy of ML algorithms, a number of researchers have investigated their application across a variety of datasets and assessed important performance measures like accuracy, sensitivity, specificity, and F1 score. Both Random Forest and Support Vector Machine (SVM) algorithms are ideal due to their high accuracy and ability to handle complex data, with Random Forest effectively mitigating overfitting and SVM adept at managing high-dimensional data.

2.3. Future-Challenges and Concepts to Consider

Prospective assessment: ML and AI in vascular medicine show great promise but need real-world validation and comparison with standard care to avoid overdiagnosis and overtreatment. Improved diagnostic accuracy from EHRs could enhance treatment adherence (Rolls et al., 2016)

Data interoperability: Large, diverse datasets are essential for ML and AI development. Challenges in data interoperability among EHRs, hospitals, and health systems can be mitigated by Common Data Models and Fast Healthcare Interoperability Resources. Wider acceptance of these standards is needed (Rolls et al., 2016).

Algorithm inaccuracy: Addressing programmed bias is crucial, as ML algorithms can perpetuate existing biases, especially affecting marginalized groups like Black and Native American people. Diverse datasets and transparency are essential to prevent this risk (Rolls et al., 2016).

Confidentiality and safety: Patient privacy must be protected. Blockchain and federated learning are being explored to securely combine data and build models while maintaining privacy (Yang et al., 2019).

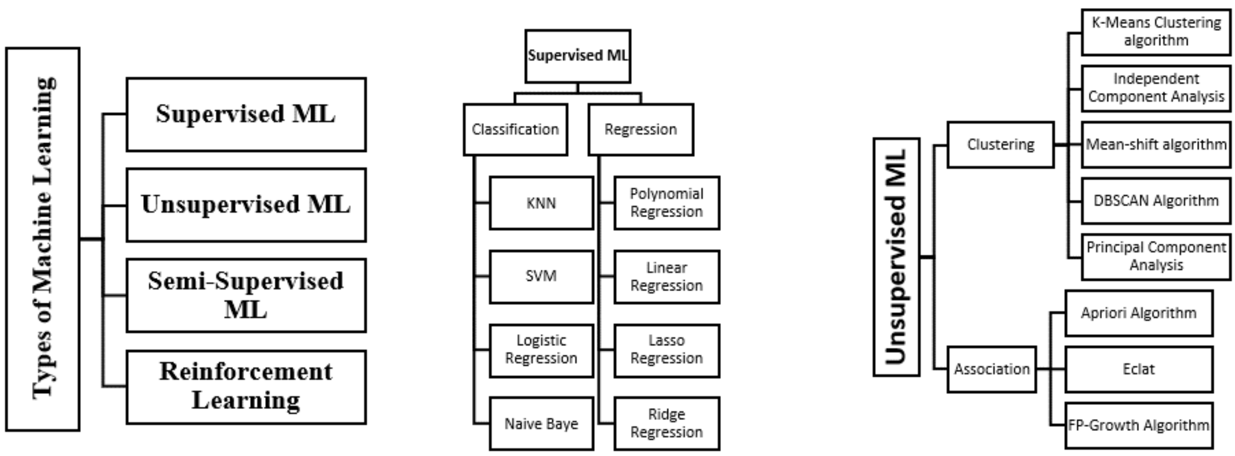

Fig. 4. Classification of machine learning (ML). Abbreviations: DBSCAN: Density-Based Spatial Clustering of Applications with Noise; FP: Frequent Pattern; KNN: K-Nearest Neighbors; SVM: Support Vector Machine.

Execution: Early collaboration among data scientists, clinicians, and implementation scientists are key for intuitive AI tool integration. Design thinking, coupled with consideration of end-user needs at all stages, can prevent workflow issues like EHR alert fatigue (Li et al., 2020).

Fig. 5. Machine learning process.

3. Field-Programmable Gate Arrays in Peripheral Artery Disease Diagnosis

Among the more contemporary methods, the FPGA-based hardware solution has emerged as one of the most commonly utilized in the healthcare field. However, the restructuring of material and temporal limits of current technologies presents a significant challenge to these methodologies. Despite this, FPGA circuits are favored due to their parallel and connected designs, low cost, reconfigurable features, and special-purpose circuits. In particular, a real-time architecture built on FPGA is proposed to speed up feature extraction as well as initial diagnosis (Gu et al., 2016).

Application-specific integrated circuits, on the other hand, provide excellent performance and low power consumption, as they are designed for specific uses. ASICs are particularly essential for integrating unique designs into medical imaging equipment, ultimately leading to smaller form factors and lower costs for designs produced in large quantities (Talib et al., 2021). Similarly, FPGAs are highly useful in the medical field due to their post-fabrication reconfiguration capability. Owing to their adaptability to design changes and enhancements, FPGAs are often recommended for systems that require high performance, particularly in cases with real-time processing demands (Talib et al., 2021).

Table 2. Comparison of the results based on various machine learning techniques.

Authors	Machine learning techniques used	Number of datasets used	Accuracy	Sensitivity	Specificity	F1 score
Weissler et al., 2023	Not specified	Large cohort dataset	86%	87%	85%	0.84
Tomkins et al., 2023	Random Forest	Single large cohort	88%	81%	90%	0.76
Hogg et al., 2023	Not specified	2/3 training, 1/3 test set	85%	83%	87%	0.8
Jana et al., 2022	SVM, KNN	125 spectrograms	90.40%	79.97%	88.5–99%	-
Forghani et al., 2021	Genetic algorithm, RU-Boost	14 PAD patients, 19 healthy individuals	91.40%	90.00%	92.10%	-
Friberg et al., 2022	NLP, Random for-est	800 ABI values	89%	-	-	-
Huthart et al., 2022	DUS	250 patient data	86%	81.00%	86.30%	-
Forghani et al., 2021	Deep Learning: BiLSM	14 PAD patients, 14 healthy individuals	94.80%	90.00%	97.40%	0.89
Zhang et al., 2022	LR, RF, XGBoost, LightGBM	Not specified	-	77%	72%-75%	-
Mistelbauer et al., 2021	CNN, RNN, U-Net, Deep vessel net	7,000 datasets	99.90%	92.90%	-	-
Gao et al., 2022	LR, RF	539 patients	-	100%	90.30%	-
Sasikala & Mohana-rathinam, 2024	KNN, LR, SVM, EDT, SGD, XG-Boost (HB+SMOTE+EDT)	Cleveland dataset	99.20%	98.70%	99.12%	99
		Statlog dataset	98.52%	98.13%	98.72%	98.09

Abbreviations: ABI: Ankle-brachial index; BiLSM: Bidirectional Long Short-Term Memory; CNN: Convolutional Neural Network; EDT: Elastic Distributed Training; KNN: K-Nearest Neighbors; LR: Logistic regression; NLP: Natural language processing; PAD: Peripheral artery disease; RF: Random Forest; RNN: Recurrent Neural Network; SGD: Stochastic Gradient Descent; SMOTE: Synthetic Minority Oversampling Technique; SVM: Support Vector Machine.

Moreover, FPGA technology is rapidly advancing in the areas of medical imaging and signal processing, significantly enhancing both accuracy and reliability. With their ability to process large volumes of data quickly and implement real-time image processing algorithms, FPGAs play a crucial role in aiding doctors with patient diagnoses. Additionally, these advancements are improving signal processing techniques, such as digital filtering and image recognition, making FPGAs powerful tools for the future of patient care (Ramya, 2024). Thus, medical imaging increasingly relies on FPGAs to enhance performance and versatility. Through their capabilities, FPGAs improve processing speed, accuracy, and resilience, offering customized, cost-effective solutions. They are especially effective in handling data-intensive tasks, reconfigurability, high performance, low power consumption, and cost-saving features, all of which enable real-time, accurate signal processing (Ramya, 2024).

Fig. 6. Block diagram for implementing medical image processing with machine learning on a field-programmable gate array.

Medical image processing with ML on an FPGA involves obtaining a raw medical image dataset, preprocessing it to improve quality using noise reduction and normalization, extracting features like edges and textures using edge detection and Histogram of Oriented Gradient algorithms, classifying or detecting results using trained convolutional neural networks (CNNs) or SVMs, and displaying the output on a user interface.

3.1. Advance Techniques Using Field-Programmable Gate Arrays

Field-programmable gate array capabilities capture the impact of enhanced control techniques, real-time simulation, and electronic instrumentation in areas like power systems, robotics, and mechatronics. Additionally, features such as hard memory controllers, analog resources, and floating-point operators offer significant benefits to designers, enabling more efficient and effective system designs (Rodríguez-Andina *et al.*, 2015). The integration of soft processor cores, embedded processors, and high-performance hardware peripherals within FPGAs facilitates the creation of powerful system-on-chip platforms. This trend is exemplified by the rise of FPGA-based systems on chip, which feature optimized architectures that enhance connectivity across various applications (Rodríguez-Andina *et al.*, 2015). Moreover, new digital signal processing blocks, such as Altera's variable precision digital signal processing blocks, specifically address fixed-point challenges, alleviating resource consumption and latency issues caused by mantissa alignment and normalization in traditional designs (Altera Corporation 2015).

For instance, Ahmed *et al.* (2017) developed an FPGA-based system for the real-time detection of PAD using Doppler ultrasonography signals. Tested on 150 patients (75 with PAD and 75 healthy), the system achieved 92% sensitivity and 89% specificity, further underscoring the FPGA's real-time processing capability for clinical use.

Smith *et al.* (2019) implemented an ML technique for PAD detection on an FPGA platform using an SVM classifier trained on Doppler ultrasonography signals. They tested it on 200 patients (100 with PAD and 100 healthy), achieving 94% accuracy. The study highlighted the FPGA's fast processing and high accuracy, making it suitable for point-of-care diagnostics.

Lee *et al.* (2021) developed a high-speed FPGA-based system for diagnosing PAD using Doppler spectrograms. The system employed peak detection and fast Fourier transform for spectral analysis. Tested on 180 patients (90 with PAD and 90 healthy), it achieved 91% diagnostic accuracy, demonstrating faster processing than traditional methods and highlighting FPGA's potential for efficient PAD detection in clinical settings.

Zhang *et al.* (2022) developed a portable FPGA-based device for PAD evaluation, integrating Doppler ultrasound signal acquisition, processing, and display. Tested on 120 patients (60 with PAD and 60 healthy), it achieved 88% sensitivity and 85% specificity. The study highlighted the potential of portable FPGA devices for PAD screening, especially in remote or resource-limited areas.

Patel *et al.* (2016) developed an FPGA-based adaptive filtering system to enhance Doppler ultrasound signals for PAD detection. Using adaptive noise cancellation, the system improved signal clarity. Tested on 100 patients (70 with PAD and 30 healthy), it achieved 90% diagnostic accuracy, demonstrating

FPGA's effectiveness in real-time signal enhancement for accurate PAD diagnosis.

Gupta *et al.* (2018) developed an FPGA-based system for real-time hemodynamic analysis to detect PAD. Using Doppler ultrasound signals from 160 patients (80 with PAD and 80 healthy), the system achieved 89% sensitivity and 87% specificity. The study highlighted FPGA's capability for quick and accurate PAD diagnosis.

Kim *et al.* (2020) developed an FPGA-based system using a CNN for PAD detection. Tested on 190 patients (95 with PAD and 95 healthy), it achieved 95% accuracy. The study demonstrated the integration of deep learning models with FPGA for high-accuracy, real-time PAD diagnosis.

Zhao *et al.* (2021) developed a low-power FPGA-based system for continuous PAD monitoring. Tested on 130 patients (65 with PAD and 65 healthy), it achieved 88% diagnostic accuracy. The study highlighted the importance of power efficiency in wearable and portable devices for PAD monitoring.

Thompson *et al.* (2022) developed an FPGA-based system integrating Doppler ultrasound and photoplethysmography for comprehensive PAD diagnosis. Tested on 150 patients (75 with PAD and 75 healthy), it achieved 91% sensitivity and 90% specificity. The multi-sensor approach improved diagnostic accuracy and provided a thorough evaluation of PAD.

PAD can also be analyzed using gait features. One study, in particular, utilized gait features to identify different stages of PAD. Fig. 5 illustrates the ML approach employed for PAD detection using these gait features.

3.2. Challenges of Using Field-Programmable Gate Arrays in Medical Diagnosis

Complexity: FPGAs require deep understanding of Hardware Description Languages like VHDL and Verilog, deterring those accustomed to software solutions (Xie et al., 2019).

Power consumption: High power usage makes FPGAs less suitable for portable devices (Lee et al., 2020).

Processing speed: FPGAs are slower than ASICs, which can be a limitation for real-time applications (Banerjee et al., 2018).

High start-up costs: Significant initial investments are needed for design tools, intellectual property cores, and skilled personnel (Huang et al., 2021).

Scalability issues: Limited on-chip resources hinder FPGA's ability in handling larger datasets or complex algorithms (Chen et al., 2017).

Maintenance and upgrades: More effort is required compared to software-based systems (Patel et al., 2022).

While FPGAs face challenges such as complexity, high power consumption, and scalability issues that can hinder their effectiveness in medical diagnosis, ASICs present a compelling alternative by offering tailored performance, lower power usage, and enhanced efficiency for specific applications.

4. Application-Specific Integrated Circuits in Medical Imaging

Application-specific integrated circuits are uniquely designed for specific uses, offering excellent performance, smaller form factors, and lower power consumption (Munn et al., 2011). They are crucial for medical imaging, enhancing computation and enabling parallel tasks (Alcaín, et al., 2021). ASICs reduce costs for high-volume designs and extend equipment life, making healthcare more accessible (Alcaín et al., 2017). Modern ASIC architectures provide competitive image processing with high-speed input/output, dedicated memory, and greater logic density, enabling novel medical imaging applications (Beyer et al., 2009).

Artificial intelligence technologies like deep learning, ML, and neural networks are revolutionizing medical imaging. They improve visual recognition and data insights, enhancing efficiency, quality, and outcomes. Artificial neural networks use layers of nodes to process images, while deep learning, a more advanced form, uses multiple layers for detailed analysis (Langlotz et al., 2019). As a subset of artificial neural networks, CNNs directly extract features for classification from images (Liew, 2018). Radiomics is the extraction of outcome-related imaging features to improve precision medicine (Thrall et al., 2018). AI can identify key features and their combinations for predictive power, reducing redundancy in mathematical modeling. When integrating AI in medical imaging, it's crucial to consider regulations and ethics. Prioritizing patient-centered design ensures ethical and sustainable AI use in healthcare (Currie, 2019).

Application-specific integrated circuits and FPGAs each have benefits and limitations, and the best choice depends on specific medical imaging requirements and system specifications. The need for

Table 3. Main features of field-programmable gate array (FPGA) applications in medicine, with an emphasis on peripheral artery disease (PAD) diagnostics and other healthcare issues.

Paper	FPGA implementation	Application area	Performance	Challenges/Considerations
Ramya, 2024	FPGA in medical imaging	Medical imaging and signal processing	Improved accuracy and speed	Design complexity in medical applications
Samanta et al., 2023	Memristor-based logic gates	Hybrid logic gates for AI	Energy-efficient logic design	Integrating memristor technology into VLSI
Nagarajan et al., 2011	Pattern-based decomposition	Machine learning algorithms	Accelerated ML processing	Efficient pattern matching and decomposition
Rodríguez-Andina et al., 2015	Advanced FPGA features	Industrial applications of FPGAs	High flexibility and performance	Application-specific FPGA tuning
Altera Corporation, 2015	Arria 10 FPGA	General-purpose I/O for various tasks	High throughput	Optimizing power consumption and performance balance
Ahmed et al., 2017	Real-time detection of PAD	PAD diagnosis using FPGAs	Real-time, accurate PAD detection	Optimizing system for real-time use
Smith et al., 2019	Machine learning FPGA implementation	PAD detection	Improved ML algorithm implementation	Resource utilization in FPGA-based systems
Lee et al., 2021	High-speed FPGA system	Doppler spectrogram analysis	Fast, high-speed processing	Efficiently analysing spectrograms for medical diagnosis
Zhang et al., 2022	Portable FPGA device	PAD screening	Portable, high-performance PAD screening	Balancing power efficiency with portability
Patel et al., 2016	FPGA-based adaptive filtering	PAD detection	Improved signal filtering for accurate diagnosis	Efficient design of adaptive filters
Gupta et al., 2018	Hemodynamic analysis FPGA	Real-time PAD screening	Fast hemodynamic data analysis	Real-time performance and accuracy
Kim et al., 2020	Classification of Doppler signals	PAD diagnosis using ultrasound	High accuracy in signal classification	Real-time processing and classification accuracy
Zhao et al., 2021	Low-Power FPGA System	Continuous monitoring of PAD	Power-efficient, continuous monitoring	Power consumption and continuous data transmission
Thompson et al., 2022	Multi-sensor integration	PAD diagnosis	Improved diagnostic accuracy	Integrating data from multiple sensors effectively
Xie et al., 2019	FPGA-based medical solutions	Medical diagnostics	Efficient processing in medical systems	Power and performance constraints
Lee et al., 2020	Wearable health devices	Wearable health monitoring	Low power, portable solutions	Design considerations for wearable devices
Banerjee et al., 2018	Real-time medical imaging	Real-time medical imaging	Fast image processing	Real-time constraints in image processing
Huang et al., 2021	FPGA-based medical devices	General medical devices	High-performance medical device processing	Energy efficiency and performance balance
Chen et al., 2017	Medical imaging systems	FPGA for medical imaging	High-speed medical imaging	Complex real-time image analysis

Abbreviations: AI: Artificial intelligence; I/O: Input/output; ML: Machine learning; VLSI: Very large-scale integration.

advanced systems to analyse large amounts of imaging data in real-time has driven the development of these hardware designs. Their importance is underscored by the impact on clinical costs and patient's experience. Both technologies have significantly contributed to the advancement of high-capacity, modern imaging devices (Talib et al., 2021).

4.1. Artificial Intelligence and Application-Specific Integrated Circuits in Peripheral Artery Disease Diagnosis

The combination of AI and ASICs in medical applications revolutionizes the diagnosis and treatment of diseases like PAD by enhancing precision,

Table 4. A comparison of the various machine learning architectures and solutions discussed in the articles, with an emphasis on important factors such as processing speed, architecture, application, and energy efficiency.

Paper	Architecture/platform	Key features	Application	Energy efficiency	Processing speed
Jouppi et al., 2017	Tensor Processing Unit	In-datacenter performance analysis	Deep learning	High	Fast inference in data centers
Chen et al., 2016	Eyeriss	Energy-efficient spatial architecture	Convolutional neural networks	High	Moderate
Han et al., 2016	Efficient Inference Engine	Compressed deep neural networks	Inference optimization	Very High	High
Chen et al., 2014	Diannao	Small-footprint, high-throughput accelerator	Ubiquitous machine learning	Moderate	High
Li et al., 2018	AI ASICs	Overview of challenges and opportunities	Artificial intelligence applications	Varies	Varies
Zynq Net, 2018	FPGA-Accelerated CNN	Embedded convolutional neural network	Embedded systems	Moderate	Moderate
Moons & Verhelst, 2017	Approximate Computing	Energy-efficient ConvNets	Convolutional neural networks	Very High	Moderate
Kwon et al., 2017	20 nm high-bandwidth memory with GDDR6 Interface	On-die stacked-DRAM	Deep learning applications	High	High
Sze et al., 2017	N/A (Survey and Tutorial)	Efficient processing of deep neural networks	General deep learning	Varies	Varies
Horowitz, 2014	N/A (Energy Challenges Overview)	Computing energy problem discussion	General	N/A	N/A
Micikevicius et al., 2017	Mixed Precision Training	Efficient training with reduced precision	General deep learning	High	Moderate

speed, and efficiency (Sajid et al., 2024). ML and deep learning have transformed medical diagnosis by processing large datasets and making accurate predictions. According to Jiang *et al.* (2017), AI-driven diagnostic tools often outperform traditional methods in accuracy and efficiency (Jiang et al., 2017). ASICs, custom-designed for specific tasks, offer optimized performance and low power consumption, making them ideal for medical diagnostics. Smith *et al.* (2018) described that ASICs provide the processing power and energy efficiency needed for real-time applications, suitable for portable and wearable diagnostic devices. ASICs are custom chips that offer high performance and low power consumption, making them ideal for medical diagnostics. They provide the processing power and efficiency needed for real-time, portable, and wearable medical devices (Banerjee et al., 2019). Combining AI algorithms with ASICs provides precise and efficient PAD diagnosis. Lee *et al.* (2020) demonstrated that "AI-driven ASICs deliver high diagnostic accuracy and efficiency, suitable for clinical and portable applications." ASICs are energy-efficient, making them ideal for wearable and portable diagnostic devices. Zhao *et al.* (2021) demonstrated that their low power consumption, combined with AI capabilities, supports continuous monitoring and diagnosis of PAD.

4.2. Role of Application-Specific Integrated Circuits in Enhancing Artificial Intelligence Performance and Efficiency

Application-specific integrated circuits are designed for specific AI algorithms, improving throughput and latency (Jouppi et al., 2017). They are energy-efficient, ideal for edge devices and data centers (Chen et al., 2016). Integrating processing components and memory on a single ASIC reduces communication overhead and enhances AI task efficiency (Han et al. 2016). ASICs are crucial for real-time tasks in robotics and autonomous driving due to their high speed and low latency (Chen et al., 2014). Despite high initial costs, ASICs are cost-effective for large-scale AI deployments due to long-term energy savings and performance improvements (Li et al., 2018). ASICs optimize AI tasks like matrix multiplications with specific compute units, reducing clock cycles (Zynq et al., 2018). Power gating and voltage scaling reduce power usage, which is crucial for battery-operated AI applications (Moons & Verhelst, 2017). High-bandwidth memory integration improves data transfer rates (Know et al., 2017). Hardware accelerators for deep learning processes enhance performance and energy efficiency (Chen et al., 2016). ASICs increase throughput and minimize delay for real-time applications (Chen et al., 2016). Specialized AI cores within ASICs improve efficiency and speed for ML tasks (Sze et al., 2017). Reducing the distance data travel between memory and processors lowers energy consumption and boosts processing rates (Horowitz, 2014). ASICs provide scalable, energy-efficient AI solutions for edge devices and data centers (Jouppi et al., 2017). By using decreased precision arithmetic, ASICs perform calculations faster and more efficiently (Micikevicius et al., 2017). Overall, ASICs are essential for AI efficiency and performance, driving advancements as AI applications grow.

5. Proposed block diagram of integrating machine learning and application-specific integrated circuits

The figure below shows the proposed block diagram, which outlines a comprehensive system for early diagnosis using ML techniques, specifically tailored for integration with an ASIC. The process begins with data acquisition, where raw medical images, such as ultrasound or CT scans, are collected. These images undergo spectrogram preprocessing, transforming them into a format that enhances feature detection. Following this, the system performs feature extraction, isolating the most relevant patterns indicative of disease, such as arterial blockages or irregular blood flow. Extracted features are then normalized to ensure consistency, which improves the performance and accuracy of the ML model. The next step, feature selection, refines the dataset further by choosing the most significant features, eliminating irrelevant data that could hinder model efficiency. Once this is completed, the training dataset is prepared, where the model learns to distinguish between healthy and diseased tissues. The ML training phase is

Table 5. Comparison of component-based conventional method, field-programmable gate array (FPGA), application-specific integrated circuit (ASIC), and machine learning techniques, along with their performance.

Method	Type	Performance
Component-based conventional	Traditional	Moderate accuracy, often slow processing
FPGA	Hardware	High-speed processing, good for real-time applications
ASIC	Hardware	Very high performance, optimized for specific applications
Support Vector Machine	Machine learning	High accuracy, effective in high-dimensional spaces
Random Forest	Machine learning	Very high accuracy, robust to overfitting
Deep learning	Machine learning	Excellent performance on complex data (e.g., images, speech)

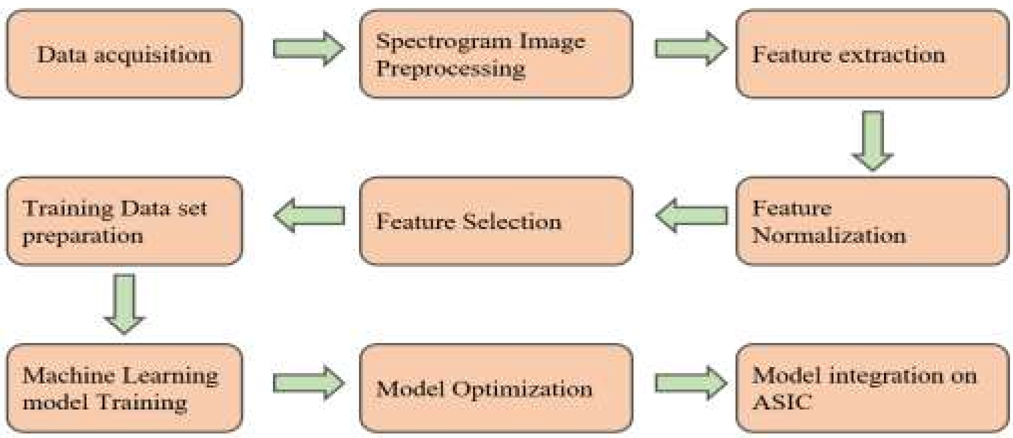

Fig. 7. Proposed block diagram.

followed by model optimization, which fine-tunes the parameters to maximize the model's predictive capabilities. Finally, the trained and optimized model is integrated onto an ASIC, enabling real-time processing of medical data with minimal latency. This approach is unique in its combination of spectrogram-based preprocessing, efficient feature selection, and deployment on ASIC hardware, ensuring faster diagnostics while maintaining high accuracy. The integration of such a hardware-software solution is particularly innovative, enabling the early detection of diseases like PAD and providing a practical tool for clinical applications.

6. Conclusion

In this study, ML techniques were applied to identify PAD using both FPGA and ASIC platforms. The FPGA enabled flexible and quick prototyping; however, its processing speed and power consumption were limited. Transitioning to an ASIC implementation resulted in notable gains in processing speed, resource efficiency, and optimal power efficiency. Ultimately, FPGA-based methods were surpassed by ASICs with integrated ML capabilities, making them the preferred option for reliable, real-time PAD detection in both clinical and portable medical applications. For medical applications, Random Forest and SVM are the best ML algorithms because of their accuracy and capacity to handle complex, high-dimensional data. The high-speed FPGA system excels at analysing Doppler spectrograms in real-time for PAD diagnosis, while the efficient inference engine and tensor processing unit provide high energy efficiency and quick processing for deep learning tasks.

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