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The Usage and Benefits of Jetson Nano for Deployment of Machine Learning Algorithms for Water Potability Prediction

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Abstract
This study analyses the benefits of NVIDIA Jetson Nano in deploying machine learning algorithms to forecast water potability. Jetson Nano will be a compact and cost-effective edge water potability analysis solution due to its powerful Graphics Processing Unit (GPU) and energy-saving architecture. Jetson Nano can handle sophisticated prediction models and improve water assessment in remote and urban settings, according to this study. Jetson Nano performs well in real-time data processing and machine learning conclusions with reduced latency by integrating sensors with data gathering systems. This study shows how Jetson Nano improves water potability prediction accuracy and reliability by reviewing case studies and testing findings. This report highlights edge AI systems' reduced cloud infrastructure dependence, cheaper operational costs, and fast response. Overall, this research shows that Jetson Nano can improve water potability monitoring and help introduce intelligent edge computing in environmental and public health.
Keywords: *Jetson Nano, Water Potability Prediction, Machine Learning, Real-time Data Processing*

1. INTRODUCTION

1.1. Background on water potability and the role of Jetson Nano

If we want to protect public health and manage natural resources well, we need to keep an eye on how potable the water is. A global goal is making sure everyone has access to clean, safe, and drinkable water, especially in places where water pollution or contamination poses serious health risks. The term "potability" describes the state or attribute of being fit for ingestion or drinking. Potability, as it relates to water, is the degree to which it is safe and sanitary enough for people to drink without risk of injury or disease [1]. Long-standing methods or processes for testing the potability of water usually involve combining lab tests, which can take a lot of time, work, and resources. Machine Learning (ML) and edge computing technologies, on the other hand, have opened new possibilities that will make the process of judging whether water is safe to drink much more efficient and accurate. These new technologies make it possible to analyse and make decisions quickly at the point where the data is collected. This greatly lowers latency and the need to rely too much on old data processing centres. NVIDIA Jetson Nano is famous for having a powerful GPU and using very little power. It is also an ideal choice for putting machine learning methods to use in edge computing settings. Additionally, Jetson Nano's small size and low cost make it perfect for remote areas and places with limited funds where modern cloud-based systems might not be easily available. So, this study looks at how Jetson Nano can be used to predict how potable water will be by processing data right away and drawing conclusions from that data using machine learning. This makes it a good replacement for older systems that check the potability of water. For example, while past research has shown that machine learning can help with water potability analysis, many of the solutions that were suggested still relied on cloud-based infrastructures, which can cause delays and come with high costs and other operational challenges. However, this study shows how the amazing features of Jetson Nano can help make water safer to drink, especially in places with limited funds, by using the power of edge computing and machine learning techniques.

1.2. History of Jetson Nano

The NVIDIA Jetson Nano is part of the NVIDIA Jetson family of products, which are designed for edge Artificial Intelligence (AI) and embedded applications. Below is table 1 presenting timeline of key events in the history of the Jetson Nano and its development:

Table 1: NVIDIA Jetson nano Timelines (https://developer.nvidia.com/)

Year	Event
2014	NVIDIA Introduces Jetson TK1: The first embedded AI platform with ARM and GPU capabilities.
2015	NVIDIA Jetson TX1: Major performance improvements for AI at the edge, targeting robotics and IoT.
2017	NVIDIA Jetson TX2: Improved power efficiency and performance for industrial AI and edge computing.
March 2019	Launch of NVIDIA Jetson Nano: Affordable AI computing platform with a 128-core Maxwell GPU.
November 2019	Jetson Nano Module Release: Production-ready module for integration into commercial products.
May 2020	NVIDIA Jetson Xavier NX: More powerful edge AI platform, offering up to 21 TOPS of AI performance.
November 2020	Jetson Nano 2GB Developer Kit: Budget-friendly version with 2GB Random Access Memory (RAM) for hobbyists and students.
2021	Software and Ecosystem Expansion: Continuous updates to JetPack SDK and growing community support for Jetson Nano applications.

As of 2024, the Jetson Nano as presented in Figure 1, remains a popular choice for edge AI and embedded systems, particularly in education, prototyping, robotics, and industrial AI solutions. Its affordability, low power consumption, and ability to handle AI inference make it a favoured platform for developers working on small-scale AI applications.

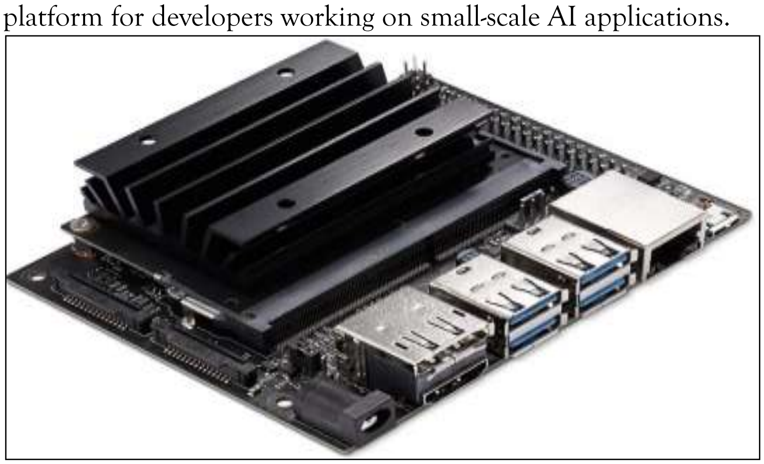

Figure 1:Figure 1: NVIDIA Jetson Nano developer kit

1.3. Research objectives

a. How can the NVIDIA Jetson Nano platform enhance the deployment of machine learning algorithms for real-time water potability prediction, and

b. What are the key benefits of using this platform in terms of energy efficiency, cost-effectiveness, and scalability in diverse environments?

2. METHODOLOGY

This systematic evaluation examines the Jetson Nano's use and benefits for water potability prediction using machine learning methods. The review used the PRISMA 2020 principles, which improve literature review transparency and completeness, to promote rigour and reproducibility [2]. PRISMA enhances reporting, reduces selection bias, and allows cross-disciplinary replicability [3]. For review process documentation, the PRISMA website (http://prisma-statement.org/) provided the checklist and flow diagrams. To synthesise relevant and high-quality materials on environmental technology, embedded AI hardware, and quantitative algorithmic performance, a systematic methodology was needed [4]. This section explains the eligibility criteria, search technique, databases, and data extraction procedures used to build a coherent and evidence-based synthesis [5].

2.1. Eligibility Criteria

The factors for eligibility were made to make sure that the studies that were chosen met the standards for quality and relevance that were needed for a systematic review. The studies were considered if they (1) came out between 2020 and 2024; (2) were written in English; (3) talked about how Jetson Nano could be used to predict the potability of water or do similar tasks using machine learning; and (4) gave clear technical evaluations or empirical results. For objective quality assessment, it looked for clear goals, good procedures, valid data, and a match between targets and results [6]. After importing BibTeX records from Harzing's Publish or Perish, Mendeley Reference Manager was used to find duplicates. These were then combined using unique identifiers. Abstract screening was done to see if the studies were relevant, and full-text screening was then done for studies that met the initial criteria. We used a special rubric to rate the depth of the research, the coherence of the ideas, and how relevant each study was to the Jetson Nano deployment scene. This was done in line with the quantitative standards pushed by [7], [8], and [9].

2.2. Information Sources

This review used authoritative environmental science, computational intelligence, and embedded systems academic databases to include transdisciplinary works. PubMed, Scopus, Web of Science, Google Scholar, Semantic Scholar, Crossref, ScienceDirect, IEEE Xplore, and ISI Web of Science. Searched sustainability, hydrology, water quality, machine learning, and sensor network journals. Engineering-focused repositories like IEEE Xplore and multidisciplinary databases like Scopus boosted study diversity and allowed citation tracking to discover influential work [10]. To standardise and compare results, all databases used the same keywords and filters [6]. Multiple sources improve methodological triangulation, synthesis dependability, and depth [3] and [11].

2.3. Search Strategy

A structured search approach was used to find all the literature that might have been relevant. Using Boolean operators, the main search string put together three important ideas: "Jetson Nano" AND "Water Potability" AND "Machine Learning." This made sure that exact papers were found that talked about embedded hardware, AI algorithms, and predicting water portability [12]. Extra filters were used to make sure that the search results only showed studies that were written in English and released between 2020 and 2024 [13]. First, titles and abstracts were looked over to get rid of anything that was obviously not relevant. Then, the full texts of studies that met the selection criteria were analysed [14]. The entire search process was documented with timestamps, search phrases, and filters to ensure consistency and repeatability [15]. It is standard practice in quantitative systematic reviews to use Boolean reasoning and controlled vocabularies. This makes the reviews more sensitive and specific. Systematic documentation also makes it possible for future researchers to use the same structure to repeat or improve the study.

2.4. Selection process

Our search tactics yielded 28 papers from specified information sources. After abstract screening, 15 papers were eliminated, leaving 13 for full-text evaluation. Based on our eligibility criteria, 7 research were included in the final dataset as presented in figure 2.

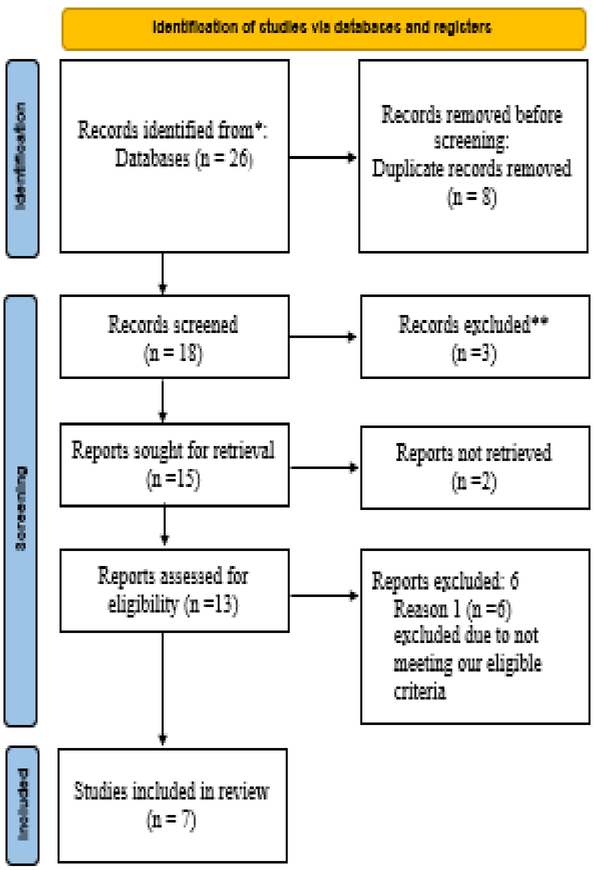

Figure 2:: PRISMA 2020 inclusion and exclusion flow diagram (edited) [Retrieved from http://prisma-statement.org/.]

2.5. Synthesis Method

The following is a histogram that shows the different approaches that were used to study how the Jetson Nano can be used to track water portability using machine learning algorithms. AI Edge Computing, Machine Learning or Deep Learning, Embedded Systems for Monitoring the Environment, Hardware Performance and Energy Efficiency, as well as general algorithm development are some of the methods that are shown in figure 3.

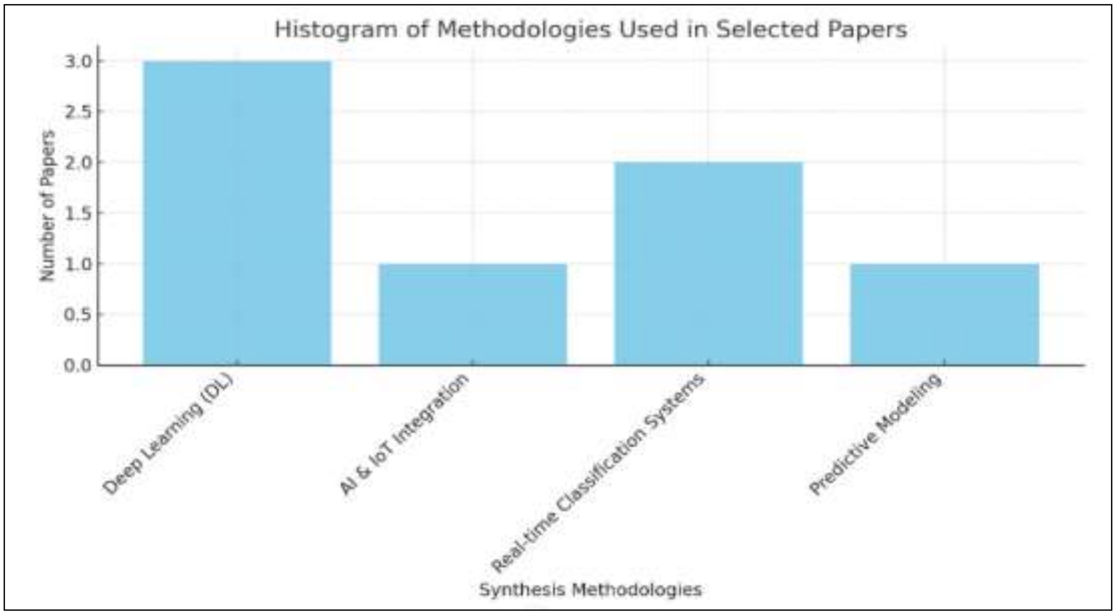

Figure 3: Synthesized Method Categories

3. FINDINGS

3.1. Benefits of Jetson Nano in Water Potability

NVIDIA Jetson Nano has shown that it is an invaluable tool that can be used across diverse domains due to its vast applicability and efficacy in concurrent edge AI applications. Below is an elaborate presentation of its applicability in diverse fields: -

i) Concurrent Algae Monitoring

Jetson Nano has been used to detect algae in real time in water studies. Jetson Nano's 0.01 seconds per image computation time and 2kbps bandwidth utilisation were praised. This makes Jetson Nano perfect for low-income areas. Jetson Nano runs AI models without compromising performance and only 5 to 10 watts. It is ideal for resource-constrained areas [16].

ii) The use of Jetson Nano in Aquaculture Monitoring

Jetson Nano has been used successfully in aquaculture systems to check the quality of the water and see how the fish behave. Furthermore, Jetson Nano can run deep learning models and has been utilised in Long Short-term Memory (LSTM) for its ability to effectively carry out complex AI tasks while consuming very little power. So, it gives useful answers to fishing issues that need making choices at the same time [17].

iii) Under Water Video Classification

under fish categorisation systems, Jetson Nano processed underwater video feeds under low-visibility circumstances. Jetson Nano maintained real-time video processing, proving its suitability for AI-based environmental monitoring [18].

iv) Deep Learning-Based Sensors in Wastewater Treatment

Jetson Nano has been used in industry. For example, it has been used to steer the flocculation process in wastewater treatment plants. Jetson Nano's built-in GPU lets it handle data at a speed of 12.8 frames per second (FPS), showing that it can be used in industrial AI tasks where multiple tasks need to be done at the same time [19].

v) AI applicability in Drowning Prevention

Jetson Nano has been used in safety-critical applications like drowning prevention; Jetson Nano has been used in processing real-time video feeds to uncover possible drowning incidents. The low-energy and concurrent AI capabilities of Jetson Nano, makes it a perfect fit for life saving detection systems like swimming pools [20].

vi) Indoor Temperature Prediction

In the aspect of building management, Jetson Nano has been utilized in predicting indoor temperatures; its compatibility with deep learning models such as GRU and CNN architectures, enables Jetson Nano to precisely predict and regulate temperature in multi-zone buildings at a time. Hence, Jetson Nano contributes significantly towards energy efficiency as well as thermal comfort in building management [21].

vii) Monitoring of Water Quality in Aquaculture

Jetson Nano also plays a significant role in monitoring water quality in aquaculture systems. Jetson Nano is very compatible with FPGA-based sensors, hence, can be used in handling very complex prediction models that are being used for real-time monitoring. Additionally, Jetson Nano provides low energy usage and accurate water quality analysis [17].

viii) Autonomous Underwater Vehicle Navigation

Jetson Nano have been used to power autonomous underwater vehicle for gas underwater seepage detection. Its outstanding concurrent processing capabilities and its ability to function in complex underwater environments, makes Jetson Nano an important tool for autonomous navigation and environmental monitoring [22].

4. Summary Review on Usage and Benefits of Jetson Nano

Low-power Jetson Nano performs real-time machine learning in environmental applications like water potability prediction. The tiny size, affordability, and integration make it ideal for field-based edge computing in water monitoring [23]. [24] showed that Jetson Nano and deep learning models like LSTM and Convolutional Neural Network (CNN) can quickly and effectively predict water quality parameters like temperature, turbidity, and pollution. Jetson Nano-based aquaculture water quality monitoring models performed well in resource-constrained areas despite processing limitations [25]. Jetson Nano edge devices offer operational continuity and minimal latency, unlike cloud-based AI systems that require constant connectivity and higher energy usage [26].

Compare Jetson Nano's pros and cons to more powerful AI systems like Jetson Xavier NX or cloud-based alternatives. Jetson Nano's 128-core Maxwell GPU struggles with deep learning and huge datasets [27]. Its simple sensor integration and energy economy make it suited for edge inference, although model simplification may reduce predicted accuracy in complicated deployments [28]. Cloud-based options are scalable but not suited for rural places with insufficient network infrastructure [29]. Therefore, Jetson Nano is best for low-cost, energy-sensitive water potability prediction applications in rural areas that require real-time processing with minimal hardware complexity [30]. Table 2 summarises the usage and benefits of Jetson Nano.

Table 2: Usage and Benefits of Jetson Nano

Research Area	**Usage**	**Benefits**	**Machine Learning Algorithms Used**	**Accuracy** *(Best Model)*	**Reference**

Real-time Algae Monitoring	Monitoring algae species in real-time with minimal computing and bandwidth needs	Low power consumption (5-10W), real-time processing, efficient resource usage	Convolutional Neural Networks (CNN), Data Augmentation	99.87% test accuracy	[16]
Aquaculture Monitoring	Analysing fish behaviour and water quality using deep learning models	Handles complex AI tasks with limited power, real-time processing	Long Short-Term Memory (LSTM), Autoencoders	f1-score of 0.68	[17]
Underwater Video Classification	Processing underwater video feeds for fish classification	Real-time processing under challenging environmental conditions	Convolutional Neural Networks (CNN)	Not specified	[18]
Deep Learning-Based Sensors	Controlling flocculation processes in wastewater treatment plants	Fast processing speed (12.8 FPS) for industrial AI solutions	Convolutional Neural Network (CNN), Regression	$R^2 > 0.9$	[19]
AI in Drowning Prevention	Detecting potential drowning incidents using real-time AI video analysis	Low-power, real-time, and effective for life-saving monitoring	Convolutional Neural Network (CNN), Video Analysis	92%	[20]
Indoor Temperature Prediction	Predicting indoor temperatures using GRU and CNN models	Real-time predictions for building management and energy-saving	Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN)	92.42%	[21]
Water Quality Monitoring	Monitoring water quality using FPGA-based systems	Efficient prediction and monitoring with low energy requirements	LSTM, FPGA-based systems	RMSE score of 1.01	[17]
Autonomous Underwater	Powering an autonomous	Robust real-time	Single Shot MultiBox	89%	[22]

Vehicle Navigation	underwater vehicle for gas seep detection	processing for autonomous navigation	Detector (SSD), Forward Looking Sonar (FLS)		

4.1. Comparison of Jetson Nano with Other Platforms

The below Table 3 presents the comparison of Jetson Nano with other platforms: -

Table 3: Comparing Jetson nano with other platforms

Parameter	**NVIDIA Jetson Nano**	**Cloud-Based Platforms (e.g., AWS, Google Cloud)**	**High-Performance Edge Devices (e.g., Jetson Xavier NX)**	**References**
Real-time ML Deployment	Performs machine learning inference locally on the edge, eliminating latency from cloud dependencies.	Cloud platforms provide high computational power but introduce latency due to network dependency.	Suitable for real-time use but can be overpowered for simpler applications.	[16];[18]
Energy Efficiency	Low power consumption (5–10W), ideal for resource-constrained environments like rural or remote areas.	High power consumption due to large data centres, not energy-efficient for edge deployments.	Consumes more power (10–21W) due to higher processing capability.	[16];[20]
Cost-Effectiveness	Highly affordable ($99 developer kit), making it accessible for small-scale projects and research.	Requires ongoing costs for cloud storage, computation, and bandwidth.	More expensive upfront than Jetson Nano, typically used for industrial applications.	[22];[16]
Scalability	Compact and portable; easy to deploy in diverse environments, from urban to rural settings.	Scalable in terms of computational resources, but dependent on internet availability.	Scalable for high-performance needs but less suited for widespread, cost-sensitive applications.	[19];[22]
GPU Capability	128-core Maxwell GPU handles complex ML tasks efficiently on edge.	Cloud platforms offer powerful GPUs (e.g., NVIDIA Tesla), but usage incurs high costs.	Superior GPUs (e.g., Volta or Ampere) for highly intensive applications.	[19]

Latency	Minimal latency as all processing occurs locally.	High latency due to the round trip to cloud servers, especially in remote areas.	Similar low-latency performance but with increased power and cost requirements.	[18]
Integration with Sensors	Easily integrates with sensors for real-time water potability monitoring, suitable for edge AI applications.	Limited sensor integration due to cloud dependency and potential network issues.	Supports advanced sensor integration but may require additional configuration effort.	[16];[19]

4.2. Advantages of NVIDIA Jetson Nano Over Other Platforms

The Table 4 below presents the advantages of Jetson Nano over other platforms: -

Table 4: The Advantages of Jetson Nano over other platforms

Category	**Advantage of NVIDIA Jetson Nano**	**Explanation**
Real-Time Processing	Local inference capabilities	Jetson Nano performs machine learning inference locally without relying on cloud infrastructure, reducing latency
Energy Efficiency	Low power consumption (5–10W)	Highly energy-efficient compared to cloud servers or powerful edge devices like Jetson Xavier NX, which consume more power
Cost-Effectiveness	Affordable price ($99)	Makes it accessible for small-scale projects, unlike cloud services with recurring costs or expensive high-performance devices
Scalability	Compact and portable	Easily deployable in diverse environments, including remote and urban areas.
GPU Capabilities	128-core Maxwell GPU	Efficiently runs machine learning and deep learning models on the edge without cloud dependency.
Sensor Integration	Supports real-time sensor integration	Allows seamless integration with sensors for real-time applications like water quality monitoring.
Latency	Minimal latency	Processes data locally, making it suitable for time-sensitive applications.
Deployment Versatility	Diverse use cases	Suitable for applications in resource-constrained environments, environmental monitoring, robotics, and more.

5. FUTURE RESEARCH

Future study should enhance Jetson Nano's usability in predicting water potability by hardware integration and software enhancement. Federated learning frameworks seem promising. Instead of raw data, these frameworks share trained model parameters between Jetson Nano devices. Decentralised water quality surveillance in sensitive locations requires private data, which this technology achieves [30]. It also makes models more adaptable to different situations. Studying further sensor fusion approaches on Jetson Nano, such as merging pH, turbidity, temperature, and conductivity sensors, could enable it to handle several data sets at once and discover abnormalities and make more accurate predictions. Low-power optimisation strategies and model compression methods like trimming and quantisation should help researchers achieve fast inference on Jetson Nano hardware with constrained resources [27]. Studies that compare Jetson Nano's performance in rural and urban water systems would help us determine its wider applications and restrictions. Finally, future research could create open-source frameworks and pre-trained models for water quality analysis on embedded AI devices to make it easier to use and faster in low-resource areas [23].

6. CONCLUSION

This review studied how the NVIDIA Jetson Nano platform increases real-time water potability prediction machine learning algorithms' energy efficiency, cost-effectiveness, and scalability. This proves Jetson Nano is a feasible edge computing solution for decentralised and resource-limited water quality monitoring. The combination of CNNs, LSTMs, GRUs, and environmental sensors allows accurate and fast water potability projections. Jetson Nano minimises latency and speeds anomaly detection by providing local inference on-device, eliminating cloud connectivity. Increasing real-time, on-site water quality analysis is the goal. Multiple studies cited the platform's low power consumption (5–10W), cost (about $99), and compact, deployable design as major benefits. These attributes make it suited for urban and off-grid rural deployment. Its energy efficiency and low infrastructure requirements reduce operational expenses compared to high-performance edge devices and cloud services. These advantages make Jetson Nano a cost-effective, scalable solution for continuous, sustainable water monitoring.

Limitations occur despite its benefits. Unlike Jetson Xavier NX or cloud-based AI servers, the device cannot manage high-volume data or train complicated models due to its limited computing capability. Model deployment on Jetson Nano sometimes involves pruning and quantisation, which may reduce accuracy. Field calibration may be needed for sensor integration, and long-term deployment studies are scarce. Federated learning architectures, multi-sensor data fusion, and adaptive optimisation algorithms should be studied to improve Jetson Nano's environmental AI applications. Open-source model libraries for water quality prediction would boost acceptance and innovation. Jetson Nano is a viable platform for real-time, scalable, and cost-effective water potability monitoring, enhancing technology and environmental health.

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