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Analysis of Inorganic Waste Classification Orange Box Based on TensorFlow Lite using Raspberry Pi 5

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ABSTRACT

While Smart City initiatives are evolving, waste management infrastructure remains a critical bottleneck, often hindered by high energy dependency and latency issues associated with cloud computing. Traditional automated solutions lack the autonomy required for scalable, outdoor deployment. **This research introduces** Orange Box a self-sustaining Edge-AI waste classifier designed to bridge the gap between high-performance computing and energy efficiency. The primary goal is to demonstrate that complex Deep Learning tasks can be executed locally on renewable energy without sacrificing classification precision. **The system orchestrates** a MobileNetV2 architecture on the Raspberry Pi 5, utilizing TensorFlow Lite (TFLite) quantization to drastically reduce computational load. Uniquely, this Green IoT node is fully decoupled from the power grid, driven by a custom power management system utilizing a 100Wp monocrystalline solar panel to sustain both the neural processing unit and robotic actuators. **Experimental benchmarks** reveal a robust 92% classification accuracy with an inference latency of just 45ms, significantly outperforming previous edge-device generations. Crucially, energy analysis validates operational autonomy for up to 72 hours without sunlight, confirming the system's reliability for continuous urban deployment. **This study demonstrates** that the convergence of quantized Edge AI and solar harvesting is not merely theoretical but a deployable standard for the next generation of Smart City infrastructure, directly advancing the Sustainable Development Goals (SDGs) for sustainable urbanization.

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1. INTRODUCTION

Inorganic waste management remains a critical challenge in modern urban environments, particularly due to the increasing volume of waste generated after the pandemic. This condition not only exacerbates environmental pollution but also highlights the limitations of conventional waste sorting systems that still rely heavily on manual processes. Such approaches are inefficient, difficult to scale, and pose significant health risks to workers. Therefore, the need for an intelligent, automated, and sustainable waste classification system has become increasingly urgent in supporting the development of smarter and more resilient cities.

Figure 1. Alignment of Orange Box Innovation with SDGs

The Figure 1 shows the alignment of the proposed Orange Box innovation with several key SDGs. This research aligns with Goal 7 (Affordable and Clean Energy) through the integration of solar-powered energy systems, enabling autonomous device operation. Furthermore, Goal 11 (Sustainable Cities and Communities) is supported by enhancing urban waste management infrastructure using smart technology [1]. In addition, Goal 12 (Responsible Consumption and Production) is promoted by improving waste sorting efficiency at the source, contributing to a more effective circular economy. These alignments highlight the broader societal and environmental impact of the proposed system [2].

Recent advancements in Smart City 5.0, Green IoT, and Deep Learning have opened new opportunities for developing intelligent waste management systems. Prior studies indicate that while IoT-based solutions improve monitoring, traditional sensor-based approaches are insufficient for complex classification tasks. Deep Learning models, particularly lightweight architectures such as MobileNetV2 optimized with TFLite, have proven effective for deployment on edge devices [3]. Furthermore, the use of Single Board Computers like Raspberry Pi 5, combined with renewable energy sources, enables real-time processing with low latency and energy efficiency. However, many existing solutions still depend on grid power or lack optimization for autonomous outdoor deployment. Therefore, this study proposes the Orange Box, a solar-powered Edge-AI system designed to perform efficient and reliable inorganic waste classification in real-world environments [4].

2. RESEARCH METHOD

The development of the Orange Box involves a holistic approach that integrates high-performance hardware components with efficient software algorithms. This comprehensive method ensures that the physical mechanisms of the bin operate synchronously with the digital decision-making process [5]. The research design prioritizes modularity, allowing each component from the power source to the inference engine to be tested and optimized independently before full system integration.

2.1. Hardware Components

The system is built using five main components designed to effectively support both image processing and mechanical actuation in an integrated manner. These components operate collaboratively to ensure that the system can perform real-time waste detection, classification, and sorting with high reliability [6]. The hardware architecture is structured to handle the computational demands of Deep Learning inference while simultaneously controlling physical mechanisms such as sensors and actuators. This integration allows the system to seamlessly connect digital intelligence with physical execution, forming a cohesive embedded system capable of autonomous operation [7, 8]. Furthermore, the modular design approach enables each component to be independently tested and optimized, ensuring flexibility for future system enhancements and scalability.

The selection of these components is critical to achieving an optimal balance between performance, responsiveness, and energy efficiency, particularly for deployment in outdoor and off-grid environments [9].

Each hardware element is carefully chosen based on its processing capability, power consumption, durability, and compatibility within the overall system architecture. In addition, the combination of processing units, sensing modules, actuation systems, and power management components is designed to minimize computational latency while maximizing energy utilization [10, 11]. This is particularly important for maintaining continuous operation under limited energy availability. By adopting a holistic hardware integration strategy, the system not only achieves efficient real-time performance but also supports the principles of sustainable, autonomous, and scalable Green IoT deployment in smart waste management applications.

2.1.1. Main Processing Unit

The core of the system is the Raspberry Pi 5, as shown in Figure 2, which serves as the primary processing unit responsible for executing image classification and system control tasks. It is equipped with a Broadcom BCM2712 quad-core Arm Cortex-A76 processor clocked at 2.4 GHz and supported by 8GB of LPDDR4X SDRAM, providing a significant performance improvement compared to the previous Raspberry Pi 4, including up to three times higher CPU performance and faster I/O speeds [12]. The board also features a dedicated UART connector and a PCIe 2.0 interface, enabling high-speed peripheral communication. This model was selected not only for its computational capability but also for its enhanced thermal management, which allows stable performance under continuous high-load operations typical in computer vision tasks, thereby minimizing CPU throttling issues [13]. Moreover, by leveraging local edge processing instead of cloud-based computation, the system significantly reduces latency, making it highly suitable for real-time waste sorting applications.

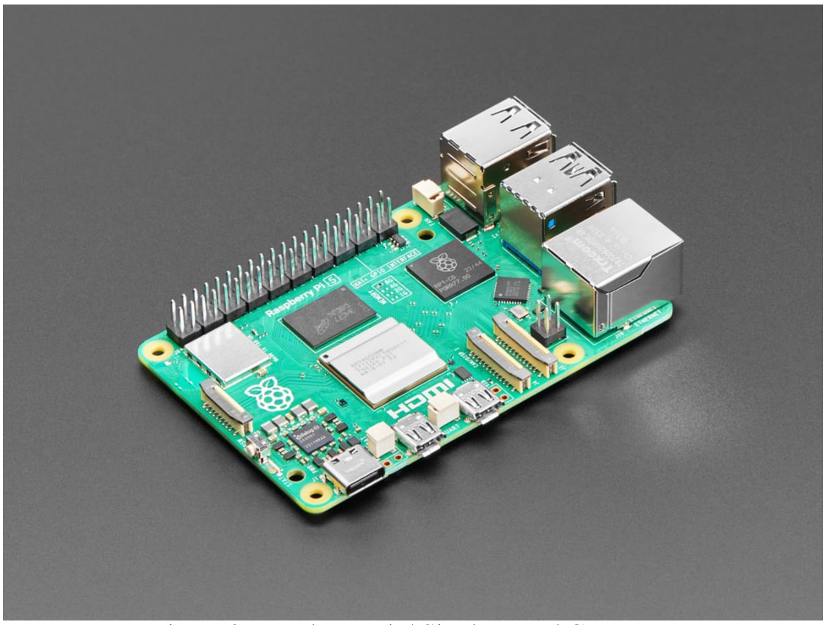

Figure 2. Raspberry Pi 5 Single Board Computer

The Figure 2 illustrates the physical form of the Raspberry Pi 5 single-board computer utilized in this system. The compact design integrates essential processing components, connectivity ports, and interfaces required for seamless interaction with sensors, cameras, and actuators. Its architecture supports efficient data processing and high-speed communication, making it suitable for real-time Edge AI applications. This hardware configuration enables the system to maintain stable performance while operating continuously in an embedded and energy-constrained environment [14].

2.1.2. Visual Sensor and Trigger

To minimize power consumption, the system utilizes an HC-SR04 Ultrasonic Sensor as a trigger mechanism, which operates by emitting high-frequency sound waves to detect the presence of waste objects within a range of approximately 20 cm, thereby activating the camera only when necessary and reducing unnecessary energy usage [15]. For image acquisition, the system employs the Raspberry Pi Camera Module V2, as shown in Figure 3, which is equipped with a Sony IMX219 8-megapixel sensor capable of capturing high-resolution images at 3280 × 2464 pixels. This camera is directly connected to the Camera Serial Interface (CSI) port, a design choice that significantly improves system efficiency compared to conventional USB-based cameras [16]. The CSI interface provides a dedicated high-speed data pathway to the GPU, effectively bypassing CPU overhead typically associated with USB data transfer. As a result, image frames can be transmitted and processed with minimal delay, ensuring faster inference time and enabling responsive real-time waste classification [17]. This combination of an intelligent triggering mechanism and an optimized image capture system plays a crucial role in maintaining both energy efficiency and high-performance operation within the embedded Edge AI environment.

Figure 3. Raspberry Pi Camera Module V2

The Figure 3 shows the Raspberry Pi Camera Module V2 utilized in this system for image acquisition. The module features a compact design with a flexible ribbon cable that enables easy integration with the Raspberry Pi board through the CSI interface. Its high-resolution imaging capability, combined with efficient data transmission, allows the system to capture detailed visual information required for accurate waste classification [18]. The lightweight and modular structure of the camera also supports flexible placement within the system, ensuring optimal positioning for object detection while maintaining overall system efficiency in real-time Edge AI operations.

2.1.3. Actuator and Driver

The sorting mechanism relies on the MG996R Servo Motor, as shown in Figure 4, which functions as the primary actuator responsible for directing waste into the appropriate category. This metal-gear digital servo is known for its high stall torque of approximately 11 kg/cm at 6V, making it suitable for handling repetitive mechanical movements in an automated sorting system [19, 20]. It operates within a rotation range of 0 to 180 degrees, which is sufficient to control the directional movement of the sorting flap, enabling it to shift left for organic waste and right for inorganic waste. The reliability and responsiveness of the servo motor are essential to ensure accurate and timely sorting actions, especially under continuous operational conditions [21]. Therefore, optimizing the servo movement is critical to prevent mechanical overshoot, reduce unnecessary vibration, and minimize long-term mechanical wear. This ensures consistent positioning accuracy and contributes to the overall durability and stability of the system during prolonged use.

To control the servo motor efficiently, the system utilizes the PCA9685 PWM Driver, as illustrated in Figure 4, which provides precise Pulse Width Modulation (PWM) signals through an I2C-based communication interface [22]. Although the Raspberry Pi includes built-in hardware PWM capabilities, the use of an external driver offers significant advantages in terms of system stability and power management. By isolating the power requirements of the servo motor from the main processing unit, the PCA9685 prevents voltage fluctuations that could potentially cause system instability or unexpected resets during operation [23]. In addition, the driver allows for smoother and more consistent signal generation, which improves the overall responsiveness of the actuation system. This approach also enhances scalability, as multiple actuators can be controlled simultaneously without overloading the main board [24, 25]. The control logic is implemented using Python, selected for its extensive libraries and strong support for embedded system development, enabling flexible, reliable, and maintainable control of the actuation process while simplifying system integration and future upgrades.

Figure 4. MG996R High-Torque Servo Motor

Figure 4 illustrates the MG996R high-torque servo motor along with its accompanying components, including mounting accessories, servo horns, and fastening screws, which are essential for mechanical integration. This servo motor serves as a critical actuator within the system, enabling precise rotational movement required for directing waste into designated categories [26]. With its robust metal gear construction and high torque capability, the MG996R is well-suited for repetitive and load-bearing operations, ensuring durability and consistent performance. Additionally, the availability of various servo horn shapes allows flexible mechanical design, facilitating efficient transmission of motion to the sorting mechanism while maintaining positional accuracy and system reliability [27].

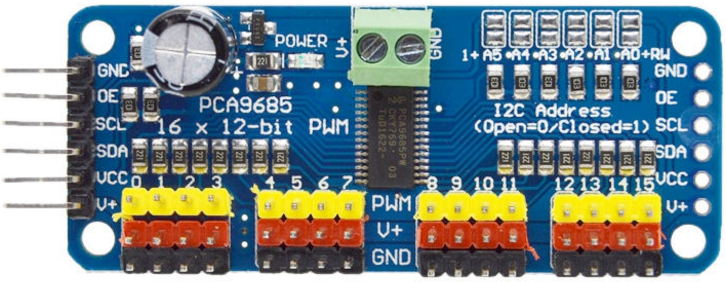

Figure 5. PCA9685 PWM Driver Module

Figure 5 presents the PCA9685 PWM Driver Module, a dedicated controller designed to generate precise PWM signals for managing multiple actuators simultaneously. This module communicates with the main processing unit via an I2C interface, enabling efficient and stable control while minimizing the computational load on the system [28]. By utilizing an external PWM driver, the system can avoid timing inconsistencies and voltage fluctuations that may occur when relying solely on the internal PWM capabilities of the microcontroller or single-board computer. Additionally, the PCA9685 supports multiple output channels, allowing scalable expansion for controlling several servo motors or other PWM-based devices. This makes it a crucial component in ensuring accurate, synchronized, and reliable actuation within the overall embedded system [29].

2.1.4. Power Management System

A key feature of the Orange Box is its off-grid capability, supported by a power system consisting of a 100Wp monocrystalline solar panel and a 12V 100Ah deep cycle LiFePO4 battery 6. This specific battery chemistry is selected due to its long cycle life and superior safety stability compared to traditional lead-acid batteries, thereby supporting sustainable circular economy goals [30, 31]. The overall energy flow within the system is regulated by a Maximum Power Point Tracking (MPPT) controller, which dynamically adjusts the input voltage to ensure optimal power extraction from the solar panel, even under conditions of partial shading.

Figure 6. 12V 100Ah Battery and 100Wp Solar Panel

Figure 6 illustrates the integration of a 12V 100Ah battery and a 100Wp solar panel as the primary components of the system's power supply, enabling fully autonomous and off-grid operation. The solar panel functions as the main energy source by converting sunlight into electrical energy, which is then stored in the high-capacity battery for continuous usage, including during periods without sunlight [32]. The selection of a 100Ah battery ensures sufficient energy storage to support prolonged system operation, while the 100Wp solar panel provides adequate power generation to maintain battery charge under typical environmental conditions. This combination not only enhances energy efficiency and reliability but also supports sustainable system deployment by reducing dependence on conventional grid electricity [33].

2.2. System Workflow

The operational logic of the Orange Box follows a sequential process designed to minimize error and maximize speed, as illustrated in the flowchart Figure 7. The process begins when the ultrasonic sensor detects an object, triggering an interrupt signal that wakes the main classification thread from idle mode [34, 35]. Once activated, the camera captures a frame which is then pre-processed (resized to 224x224 pixels) and normalized. The AI model subsequently classifies the image, and based on the result, a signal is sent to the PCA9685 driver. The servo then rotates to the designated angle, directing the waste to the appropriate bin.

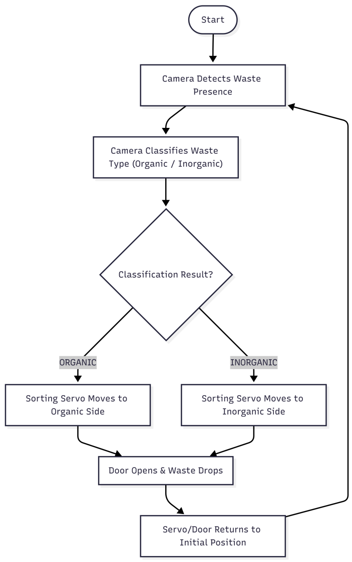

Figure 7. Flowchart of the Proposed Waste Classification System

Figure 7 illustrates the flowchart of the proposed waste classification system, depicting the sequential operational process from detection to final sorting. The workflow begins with the ultrasonic sensor detecting the presence of an object, which then triggers the system to activate the camera for image capture [36]. The captured image undergoes preprocessing, including resizing and normalization, before being analyzed by the AI-based classification model. Based on the classification result, a control signal is sent to the actuator through the PWM driver, prompting the servo motor to rotate to a specific position [37]. This movement directs the waste into the appropriate category, ensuring an automated and efficient sorting process. The flowchart highlights the integration of sensing, processing, and actuation components, demonstrating how the system achieves real-time, accurate, and autonomous waste classification.

3. FINDINGS

The results of this study demonstrate the effectiveness of the proposed Orange Box system in performing automated waste classification through the integration of Edge AI and sustainable energy solutions [38]. The evaluation focuses on key aspects such as classification accuracy, system responsiveness, energy consumption, and overall operational reliability under real-world conditions. By analyzing both quantitative performance metrics and practical implementation outcomes, these findings provide a comprehensive understanding of how the system performs in terms of efficiency, precision, and feasibility for continuous deployment in smart waste management environments [39, 40].

3.1. Model Accuracy and Performance

Field testing was conducted using 50 physical trials to evaluate the system's sorting capability. The dataset consisted of 25 organic samples (food scraps, leaves) and 25 inorganic samples (plastic bottles, plastic cups, paper). The MobileNetV2 model running on the Raspberry Pi 5 achieved an overall accuracy of 92%, correctly classifying 46 out of 50 items [41]. The confusion matrix shows balanced performance, with 23 correct classifications and 2 misclassifications in each category, resulting in precision and recall values of 92% for both classes. This indicates that the system performs consistently without bias toward a specific waste type.

In terms of computational performance, the quantized TFLite model achieved an average inference latency of 45 ms, significantly faster than standard TensorFlow models, which typically require 150–200 ms on similar hardware. This improvement enables efficient real-time processing, while the Python-based control logic adds minimal overhead. Overall, the results demonstrate that the system is capable of delivering accurate and responsive performance for real-time waste sorting applications.

3.2. Error Analysis and Environmental Factors

While the 92% accuracy is highly promising for a prototype, the remaining 8% error rate (representing 4 misclassified items out of 50) warrants detailed analysis. The primary cause for the 4 failures was identified as varying illumination conditions and object deformation.

Two inorganic items were misclassified as organic likely due to low-light scenarios creating shadows that obscured the object's features, confusing the CNN model. Conversely, the two organic items misclassified as inorganic were likely due to unusual shapes that mimicked rigid objects. This aligns with recent findings that complex illumination and occlusion remain major hurdles for CNN-based object detection in outdoor environments. This limitation suggests that future iterations should include a dataset augmentation strategy that specifically targets deformed and occluded objects to improve robustness.

3.3. Energy Consumption Profile

The integration of the 100Wp solar panel successfully fully charged the battery within 4.5 hours of peak sunlight. The system consumed approximately 15W during active sorting and only 2W during idle mode. This low idle consumption is critical for sustainability. However, the reliance on $LiFePO_4$ batteries requires careful end-of-life planning. Recent research highlights that without proper recycling protocols, battery waste can undermine the circular economy goals of green IoT projects. The current setup proves its viability for deployment in public parks without electrical outlets, validating economic analyses favoring standalone smart waste systems regarding circular economy efficiency.

3.4. Comparison with Previous Studies

To further evaluate the proposed system, a comparative analysis is conducted against previous studies in the field of smart waste management. This comparison aims to highlight the key differences in methodology, hardware capability, and energy sources used across various approaches, providing a clearer understanding of the advancements introduced by the Orange Box.

Table 1. Comparison of Orange Box with Previous Studies

Method	**Device**	**Power Source**
Ultrasonic Sensors	Arduino	Grid Power
CNN (YOLO/SSD)	RPi 3/4	Grid Power
IoT Monitoring	ESP32	Grid Power
MobileNetV2	RPi 5	Solar (Off-grid)

Table 1 highlights the novelty of the Orange Box in comparison to existing smart bin innovations by clearly demonstrating its advancements in both computational capability and energy sustainability. Unlike earlier systems that primarily relied on basic sensor-based approaches or less powerful processing units, the proposed system leverages the enhanced performance of the Raspberry Pi 5 to support more complex and accurate deep learning-based classification. In addition, the integration of a solar-powered energy system enables full energy independence, eliminating reliance on conventional grid power and allowing for flexible deployment in outdoor or remote environments. This combination of high processing power and off-grid capability represents a significant step forward from previous studies, positioning the Orange Box as a more scalable, efficient, and sustainable solution for modern smart waste management applications.

3.5. Implementation Challenges

Deploying the Orange Box in a real-world environment presents challenges that extend beyond technical accuracy and system performance. One of the primary issues lies in community behavior, where inconsistent waste sorting habits remain a significant barrier to the effective adoption of smart waste technologies. In many cases, users may not follow proper disposal practices, which can reduce the overall efficiency of the system despite its high classification accuracy. This indicates that technological innovation alone is not sufficient, and must be supported by public awareness, education, and behavioral change initiatives to ensure optimal utilization.

Furthermore, integrating this system into existing urban infrastructure requires a more people-centric approach, as emphasized in emerging Smart City 5.0 frameworks for developing countries. Successful implementation depends on how well the technology aligns with social, cultural, and operational contexts within the community. Factors such as user acceptance, accessibility, maintenance, and collaboration with local authorities play a crucial role in long-term sustainability. Therefore, addressing these socio-technical challenges is essential to ensure that the Orange Box can be effectively adopted, scaled, and integrated into broader smart city ecosystems.

4. MANAGERIAL IMPLICATION

The implementation of the Orange Box provides significant managerial implications for stakeholders involved in urban waste management, particularly municipal authorities and institutional administrators. By automating the waste classification process, the system can substantially reduce reliance on manual labor, leading to lower operational costs and improved efficiency. This allows organizations to reallocate human resources toward more strategic and supervisory roles, while also minimizing human error in waste sorting. Additionally, the automation process contributes to faster waste handling, which is essential in high-density urban environments where waste accumulation is a critical concern.

From a health and safety perspective, the adoption of this system helps reduce direct human interaction with potentially hazardous waste materials. This is particularly important in maintaining occupational safety standards and minimizing exposure to health risks associated with improper waste handling. Furthermore, the integration of Edge AI technology enables real-time decision-making at the device level, ensuring quick response times without dependence on cloud connectivity. This capability enhances system reliability and makes it suitable for deployment in various locations, including areas with limited internet infrastructure.

Strategically, the use of a solar-powered, off-grid system supports sustainability goals and aligns with green policy initiatives increasingly adopted by governments and organizations. The availability of real-time data generated by the system also opens opportunities for data-driven decision-making, such as optimizing waste collection routes and monitoring waste generation patterns. In the long term, this can improve overall resource management and support the development of smarter, more sustainable cities. Therefore, the Orange Box not only offers technological benefits but also provides a practical framework for advancing efficient, safe, and environmentally responsible waste management practices.

5. CONCLUSION

This study successfully demonstrates the development and implementation of the Orange Box as an intelligent waste classification system that integrates Edge AI with sustainable energy solutions. By leveraging a MobileNetV2 model deployed on a Raspberry Pi 5 and optimized using TFLite, the system is capable of performing real-time waste classification with high efficiency. The integration of a solar-powered, off-grid energy system further strengthens its applicability for autonomous deployment in various environments, particularly in areas with limited access to conventional power infrastructure.

The findings indicate that the proposed system achieves a high classification accuracy of 92%, with an average inference latency of 45 ms, confirming its effectiveness for real-time applications. The system also demonstrates balanced performance across different waste categories, with minimal misclassification primarily influenced by environmental factors such as lighting conditions and object deformation. In addition, the energy consumption analysis shows that the system operates efficiently under both active and idle conditions, while maintaining reliable performance through its solar energy integration. These results validate the feasibility of combining lightweight deep learning models with edge computing and renewable energy to address real-world waste management challenges.

Future research and innovation can focus on enhancing the robustness and scalability of the system by expanding the dataset to include more diverse waste categories, such as glass, metal, and hazardous materials. Improvements in model performance can also be achieved through advanced data augmentation techniques and the integration of adaptive learning mechanisms to handle varying environmental conditions. Furthermore, the development of a cloud-connected monitoring dashboard and IoT-based analytics platform would enable real-time data visualization and more informed decision-making for waste management authorities. These advancements would not only improve system performance but also contribute to the broader adoption of sustainable, intelligent solutions in smart city ecosystems.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: QA; Methodology: FJ; Software: HZ; Validation: QA and AF; Formal Analysis: QA and HA; Investigation: HZ; Resources: QA; Data Curation: AF; Writing Original Draft Preparation: FJ; Writing Review and Editing: QA, AF, and HA; Visualization: HZ. All authors, QA, AF, HA, and FJ and HZ have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

As part of our commitment to transparency, the dataset used in this study is openly available via the Zenodo Repository https://zenodo.org/records/19352409

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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