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DESIGN AND IMPLEMENTATION OF A SOLAR-POWERED AUTONOMOUS DRAIN-CLEANING ROBOT WITH IOT AND VISION-BASED DEBRIS DETECTION

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ABSTRACT

Drain blockages caused by dried leaves and debris are a recurring issue in residential areas, particularly in tropical regions such as Malaysia leading to hygiene risks and increased manual maintenance effort. This paper presents the design and implementation of a solar-powered autonomous drain-cleaning robot for domestic applications. The system integrates a mobile robotic platform with a 4-DOF robotic arm, YOLOv8-based vision for real-time debris detection, and Internet of Things (IoT)-based remote monitoring. The robot is built on a Raspberry Pi 5 and incorporates VL53L0X time-of-flight (ToF) sensors, INA219 power sensors, NEO-6M GPS and a USB webcam. Detected debris triggers an automated scooping sequence executed by the robotic arm. Power is supplied by an 11.1 V, 5200 mAh LiPo battery, supplemented by a 12 V, 3.6 W solar panel, with telemetry transmitted via MQTT. Experimental results show that the YOLOv8 model achieved a mean Average Precision (mAP@0.5–0.95) of 88%, with stable operation at 2.0–3.5 frames per second (FPS) and approximately 1.12 h of continuous runtime per charge (57.72 Wh). Solar charging replenished 6.48% of battery capacity (3.74 Wh) within 2 h, reducing reliance on grid electricity. These results demonstrate a measurable, energy-efficient, and cost-effective solution that contributes to SDGs 6, 9, 11, and 13.

***Keywords**: Drainage robotic, machine learning, IoT, YOLOv8, solar power, object detection.*

INTRODUCTION

Drainage systems in residential areas often experience severe clogging from accumulated dried leaves and debris, especially in tropical regions such as Malaysia. Severe drain blockages and inadequate maintenance contribute to urban flooding, which has resulted in estimated economic losses of up to RM20 billion during major flood events in Selangor, Malaysia during 18–22 December 2021 [1]. This issue, if left unaddressed, contributes to localised flooding, foul odours, and increased risks of vector-borne diseases. The existing manual cleaning methods are labour-intensive, inefficient, and often neglected in household settings. Hence, there is a growing need for an automated, efficient, and affordable drainage maintenance solution.

The main objective of this study is to design and implement a solar-powered autonomous robot capable of detecting, collecting, and removing dried leaves from household concrete drains. The robot integrates computer vision, IoT, robotic actuation, and solar energy to function autonomously with minimal human intervention. The scope of this study includes the development of a 4-DOF robotic arm mounted on a mobile platform, real-time object detection using YOLOv8, remote monitoring through VIAM and MQTT, and energy autonomy through solar recharging. The robot is tailored specifically for narrow, dry, half-round household drains commonly found in residential neighbourhoods.

RELATED WORK

Recent research in drainage robotics has primarily focused on autonomous inspection and perception systems enabled by advances in robotics and artificial intelligence (AI). Previous studies have demonstrated robust drain inspection using advanced locomotion and sensing architectures. For example, the Raptor robot presented by Muthugala et al. [2] achieved stable navigation in confined sewer environments but was designed mainly for inspection rather than debris removal.

Further work integrated computer vision and machine learning to enhance perception. AI-enabled inspection frameworks that employed convolutional neural networks (CNNs) and simultaneous localisation and mapping (SLAM) to detect blockages and structural defects with high accuracy [3]. Another study further validated deep learning–based waste detection in dynamic environments [4]. More recently, previous studies have demonstrated the feasibility of deploying YOLOv8-based object detection on embedded edge platforms such as Raspberry Pi, achieving real-time inference with acceptable accuracy and latency [5]-[6]. However, these systems largely focus on inspection or surface-level waste detection and do not address autonomous debris extraction in narrow domestic drains.

Renewable energy integration has been explored by Naveen et al. [7] and Amin [8], discussing the feasibility of solar-powered outdoor operations and improved energy sustainability. IoT-enabled platforms have further enabled remote monitoring and cloud-based supervision [9]-[10], yet many such systems prioritise monitoring and data visualisation over fully autonomous cleaning.

Overall, existing studies address inspection, perception, energy sustainability, and IoT connectivity largely in isolation (Table 1). There remains a gap in a compact system that integrates real-time vision-based debris detection, autonomous mechanical removal, solar-assisted power management, and IoT-based monitoring for domestic drains. This work addresses this gap by unifying these elements into a single autonomous drain-cleaning platform.

Table 1 Comparison of existing drainage robotics systems

Ref.	Vision / AI	Power	IoT
[2]	CNN-based	Battery	Limited
[3]	CNN + SLAM	Battery	Yes
[4]	Deep Learning	Battery	No
[5]-[6]	YOLOv8 (Edge AI)	Battery	No
[7]-[8]	No	Solar + Battery	No
[9]-[10]	No	Solar + Battery	Cloud-based
This work	YOLOv8	Solar + Battery	MQTT + Cloud

SYSTEM ARCHITECTURE

The proposed autonomous drain-cleaning robot is composed of three tightly integrated subsystems: mechanical, electrical, and software. Figure 1 illustrates the overall data and control flow between these subsystems. Mechanically, the robot is built around a custom-designed 2-wheel-drive chassis modelled in Fusion 360. The chassis supports a solar panel mount and a front-mounted 4-DOF servo-driven robotic arm for debris collection. The computer-aided design (CAD) model enables accurate visualisation of component placement.

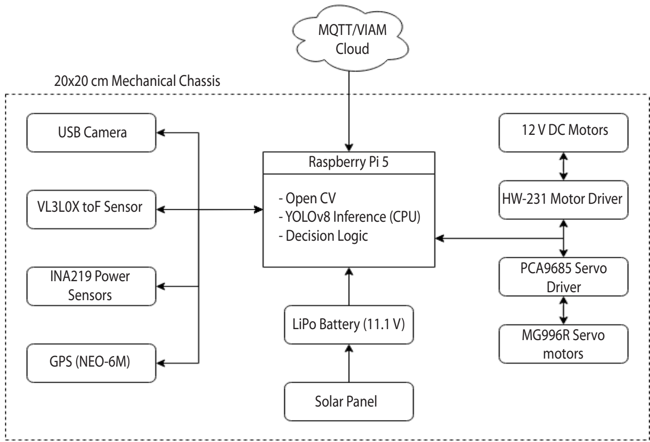

Figure 1 System block diagram

Electrically, a Raspberry Pi 5 serves as the main processing and control unit. The platform interfaces with dual 12 V direct current (DC) motors together with an HW-231 motor driver for locomotion, MG996R servo motors for arm actuation, and multiple sensors. Power monitoring and energy management are handled by INA219 current sensors, while VL53L0X ToF sensors support obstacle detection. A USB camera provides real-time visual input for debris detection. Actuation signals for the robotic arm are generated through a PCA9685 servo driver, with regulated power distribution and level shifting to ensure stable operation.

The software subsystem is implemented in Python, integrating OpenCV for video capture and preprocessing, a YOLOv8-based object detection model

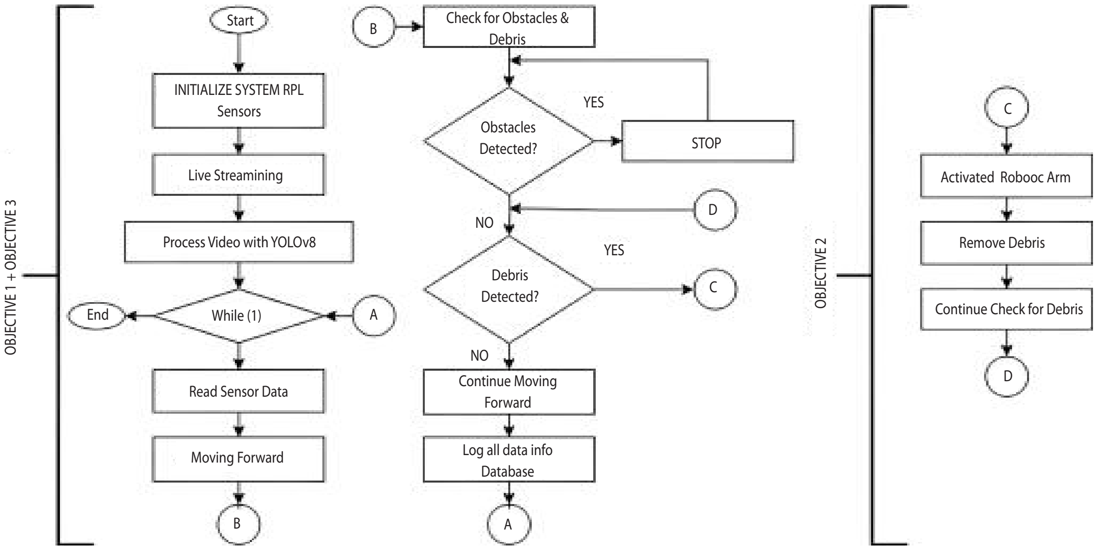

Figure 2 System-level data and control flow

for debris identification, and the VIAM framework for cloud connectivity and remote monitoring. System telemetry, including detection events and power status, is transmitted via MQTT. Figure 2 summarises the sensing–decision–actuation loop executed during autonomous operation.

Mechanical Subsystem

The mechanical subsystem was designed in Fusion 360 and consists of a 2-wheel-drive base supporting the robotic arm and the solar panel mount. The 4-DOF robotic arm is mounted at the front of the chassis to maximise reach into drainage channels. Joint lengths, servo orientations, and mounting angles were calibrated to enable efficient debris scooping while avoiding self-collision.

The robot structure combines aluminium profiles for load-bearing components and PLA-based 3D-printed parts for custom mounts and brackets, achieving a balance between structural rigidity and lightweight mobility. Figure 3 presents the complete CAD assembly of the robot.

Electrical Integration

The electrical subsystem integrates the Raspberry Pi 5 with a PCA9685 servo controller, HW-231 motor drivers, INA219 current sensors, VL53L0X ToF sensors, and a NEO-6M GPS module. The system is powered by an 11.1 V LiPo battery, with voltage regulation to safely supply both motor drivers and logic-level components.

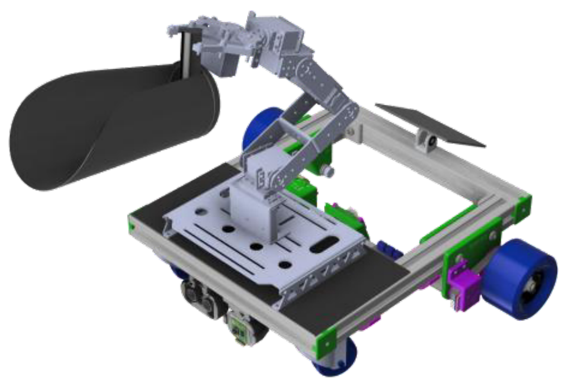

Figure 3 CAD model of the autonomous drain-cleaning robot, showing chassis, robotic arm, and solar panel placement

Wiring follows standard embedded-system practices, including colour-coded and labelled connections to improve maintainability and safety. Figure 4 illustrates the complete circuit schematic, including power distribution, sensing modules, and actuation interfaces.

Object Detection and Embedded Inference Constraints

The YOLOv8n object detection model was trained to identify dried leaves using a dataset of 1,000 pre-labelled images obtained from Roboflow and exported in YOLO format. During operation, real-time video frames are captured via a USB webcam and processed onboard the Raspberry Pi 5. To accommodate embedded hardware constraints, the YOLOv8-Nano variant was selected to balance detection accuracy and inference latency.

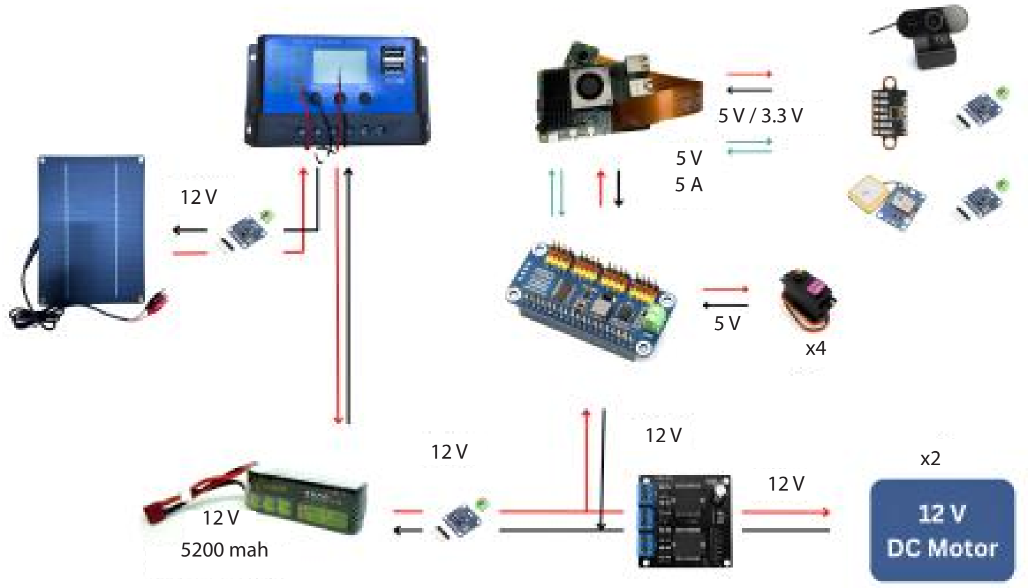

Figure 4 Electrical schematic of the robot, showing power distribution, sensing modules, and actuation interfaces

Experimental measurements indicate an average inference latency of approximately 280–350 ms per frame, corresponding to 2.0–3.5 FPS during continuous operation. Central processing unit (CPU) utilisation ranged between 65–80% during inference, with memory usage remaining below 3.2 GB. All inference was performed on the CPU without dedicated graphics processing unit (GPU) acceleration, ensuring stable operation within thermal limits.

Detection results with confidence scores above a threshold of 0.5 trigger the cleaning routine, while low-confidence detections are discarded to reduce false activations.

Cleaning Routine and Control Logic

Upon confirmed debris detection, the robot executes a predefined cleaning routine implemented in the function perform_custom_cleaning_sequence(). The sequence consists of coordinated actions, including chassis repositioning, robotic arm base rotation, shoulder elevation, elbow articulation, and wrist-based scooping. After debris collection, the arm returns to its default pose to resume navigation.

FINDINGS

The robot was constructed using a modular approach. The chassis, arm, and solar holder were 3D printed using PLA material. The CAD model guided assembly, and the fully assembled robot is shown in Figure 5. Motors and sensors were mounted using screws and brackets. Python scripts for sensor interfacing, image processing, and actuator control were uploaded to the Raspberry Pi. The VIAM dashboard was configured for real-time monitoring and live streaming.

Figure 5 Assembled autonomous drain-cleaning robot prototype

Power and Runtime

To evaluate energy efficiency and battery performance, the robot was tested outdoors with solar charging enabled. A fully charged 11.1 V 5200 mAh LiPo battery powered the system continuously, supporting object detection, Wi-Fi video streaming, and robotic arm movements. During testing, the battery voltage dropped from 12.5 V to 12.0 V (a 0.5 V drop) in 30 min, which closely aligned with the theoretical consumption rate of an estimated 0.7 V drop over the same period.

The 12 V 3.6 W solar panel contributed an average of 1.87 W under direct sunlight. Although the panel could not maintain the battery charge under full load, it extended the overall operation time by approximately 3–5 min. Performance data is summarised in Table 2.

Table 2 Power consumption and runtime characteristics

Parameter	Measured Value
Battery Capacity (Wh)	57.72
Average System Power (W)	51.5
Continuous Runtime (h)	1.12
Average Solar Charging Power (W)	1.87
Energy Recharged in 2 h (Wh)	3.74
Battery Replenishment (%)	6.48

AI Model Performance

Performance evaluation of the trained YOLOv8n model was conducted on live webcam input using the Raspberry Pi 5 in real residential drain environments under varying lighting conditions. The training dataset comprised 1,000 labelled images of dried leaves curated and annotated using Roboflow, with an 80:20 split for training and validation.

Model performance was assessed exclusively on the 200-image validation set. The YOLOv8n model achieved a precision of 99.3%, a recall of 99.9%, and a mean Average Precision of 95.6% at IoU 0.5, with an overall mAP@0.5–0.95 of 88.0%. These results indicate high detection reliability while maintaining robustness against false positives in cluttered drain environments.

Inference was performed entirely on the Raspberry Pi 5 CPU without hardware acceleration. Measured inference latency ranged from 280 to 350 ms per frame, corresponding to an effective processing speed of 2.0–3.5 frames/s. Although lower than desktop-class systems, this throughput was sufficient to support timely debris detection and trigger autonomous cleaning actions. Latency measurements across repeated trials demonstrated consistent runtime behaviour, confirming the suitability of the model for embedded real-time deployment.

Performance evaluation of the trained YOLOv8n model was conducted on live webcam input using the Raspberry Pi 5 in real residential drain environments under varying lighting conditions. The training dataset comprised 1,000 labelled images of dried leaves curated and annotated using Roboflow, with an 80:20 split for training and validation. Images were collected across diverse backgrounds and illumination levels to improve generalisation.

Model performance was assessed exclusively on the 200-image validation set. As summarised in Table 3, the YOLOv8n model achieved a precision of 99.3%, a recall of 99.9%, and a mean Average Precision of 95.6% at IoU 0.5, with an overall mAP@0.5–0.95 of 88.0%. These results indicate high detection reliability while maintaining robustness against false positives in cluttered drain environments.

Table 3 YOLOv8 object detection performance on the dried leaf dataset

Metric	Value
Precision (%)	99.3
Recall (%)	99.9
mAP@0.5 (%)	95.6
mAP@0.5–0.95 (%)	88.0
Inference Speed	2.0–3.5 frames/s
Inference Latency (ms)	280–350

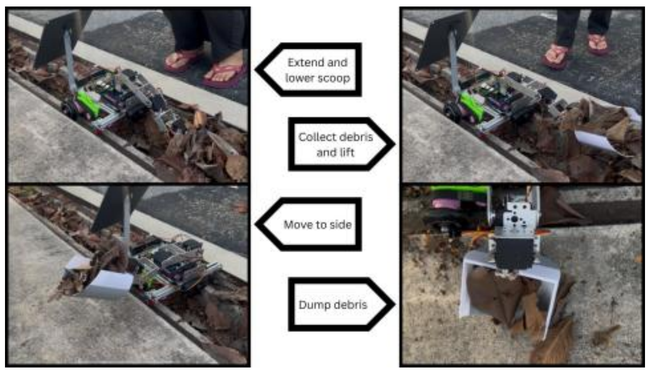

Figure 6 Sequence of autonomous debris collection during field testing in a residential concrete drain

Field Testing

Field testing was conducted in real concrete drains to evaluate the robot's practical performance. The autonomous system successfully identified dried leaves using the on-board YOLOv8 detection model and initiated the cleaning sequence in cycles lasting 30–40 s per debris instance. Obstacle avoidance mechanisms were triggered effectively when objects were detected within a 20 cm range, enabling safe navigation.

Real-time monitoring was achieved through a VIAM-based MQTT dashboard that streamed a live video feed alongside telemetry data from ToF distance sensors, power sensors, and GPS modules. This allowed remote observation and verification of cleaning events and system behaviour. The robot's physical operation during field deployment is shown in Figure 6, while Figure 7 displays the object detection interface during active cleaning.

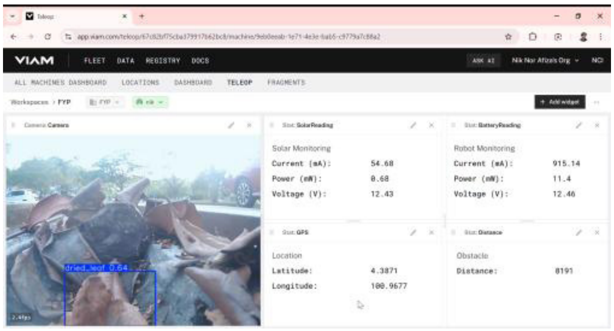

Figure 7 Real-time YOLOv8-based dried leaf detection during outdoor drain testing using the VIAM monitoring interface

DISCUSSION

The experimental results demonstrate that the proposed robot successfully achieves its primary objectives of autonomous debris detection, mechanical removal, and IoT-enabled monitoring in domestic drain environments. The YOLOv8-based vision system achieved a mean Average Precision (mAP@0.5–0.95) of 88%, confirming its suitability for real-time debris detection on embedded hardware. This performance reflects a deliberate trade-off between detection accuracy and computational efficiency, as the YOLOv8-Nano model was selected to ensure acceptable inference latency on the Raspberry Pi 5. While higher-capacity models could potentially improve accuracy, they would significantly increase energy consumption and reduce operational stability on resource-constrained platforms.

Table 4 Bill of materials

Component	Cost (RM)
Raspberry Pi 5 (4GB)	295.00
USB Camera	25.00
VL53L0X ToF Sensor	15.00
INA219 Power Sensors (×2)	15.00
NEO-6M GPS Module	17.00
MG996R Servo Motors (×4)	80.00
12 V DC Motors (x2)	50.00
HW-231 Motor Driver	100.00
PCA9685 Servo Driver	70.00
Solar Panel (12 V, 3.6 W)	40.00
LiPo Battery (11.1V, 5200mAh)	120.00
Chassis + Mechanical Parts	250.00
Total Cost	1,077.00

A similar trade-off is observed between operational speed and mechanical precision. The robotic arm completed each cleaning cycle within 30–40 seconds, balancing reliable debris grasping with controlled servo motion to avoid mechanical interference. Faster actuation could reduce cycle time but may compromise positioning accuracy and increase wear on servos. Occasional navigation difficulties in narrow or uneven drains further highlight the limitations of the current locomotion design, where constrained ground clearance and limited path adaptability affect autonomy.

From an energy perspective, the system achieved an average runtime of approximately 1.12 h under full load. Although solar assistance contributed to partial battery re-plenishment, the measured average solar input of 1.87 W was insufficient for sustained continuous operation. This underscores the trade-off between system compactness and energy autonomy. Compared to several published drain inspection robots that rely solely on battery power, the proposed system introduces support for renewable energy; however, its contribution remains modest due to panel size constraints.

In addition to performance considerations, practical deployment viability is influenced by system cost. As summarised in Table 4, the total hardware cost of the proposed prototype is RM1,077.00, reflecting a balance between functionality and affordability. Compared with commercial drain inspection or cleaning systems, which typically incur substantially higher costs, the proposed solution offers a cost-effective alternative for residential applications while integrating autonomous cleaning, embedded AI, and IoT connectivity.

Compared with existing inspection-oriented systems re-ported in the literature, which primarily focus on perception and monitoring, the proposed robot offers an integrated solution combining vision-based detection, active debris removal, and cloud connectivity within a single platform. While some reported systems achieve higher mobility or longer endurance, they often lack autonomous cleaning capability or renewable energy integration.

Future improvements will focus on enhancing system autonomy and robustness. Planned upgrades include the integration of multi-camera setups or LiDAR sensors for improved depth perception, adaptive path-planning algorithms for navigating constrained drain geometries, and higher-efficiency solar panels or hybrid energy storage solutions. These enhancements aim to improve detection reliability, mobility, and operational endurance, further advancing the practicality of autonomous drain-cleaning systems for domestic applications.

CONCLUSION

The proposed Domestic Household Drain Cleaning System demonstrates a practical, autonomous solution for debris detection and removal in residential drainage environments. By integrating computer vision, solar-assisted power management, IoT-based monitoring, and robotic actuation into a compact and cost-effective prototype, the system validates its technical feasibility for real-world deployment. Experimental results confirm reliable debris detection performance and stable autonomous operation within embedded hardware constraints, supporting its readiness for practical use. The system aligns with smart city and sustainable urban automation initiatives by reducing reliance on manual drain cleaning and by introducing support for renewable energy. Based on measured operational performance, the proposed solution has the potential to reduce manual drain cleaning effort by approximately 30–40% in routine residential maintenance scenarios, particularly for surface-level debris such as dried leaves. Future work will focus on improving robustness under diverse lighting and weather conditions through expanded YOLOv8 training datasets, refining wiring and power distribution for enhanced hardware safety, and further optimising system autonomy and energy efficiency to support longer deployment durations.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

AUTHORS' CONTRIBUTION

Nik Nor Afiza Che Isa led the experimental work, data analysis, and manuscript preparation. Nor Zaihar Yahaya provided supervision, conceptual guidance, and critical review of the manuscript. All authors read and approved the final version of the manuscript.

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